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Perceptual Constraints and the Dynamics of Movement Execution and Learning

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Guidance by simple visual patterns has been reported to facilitate performance of difficult coordination patterns, supposedly by overriding coordination constraints that limit stable bimanual coordination to in-phase and anti-phase. With perceptual simplification, complex movement details would be naturally tuned in for execution. Movement organization, however, might not have the same dynamical requirements in visually guided performance compared to performance under usual perceptual conditions. Research reported here had two goals: (1) assess potential differences in the dynamics of coordination under different perceptual conditions; (2) relate dynamical characteristics of coordination under different perceptual conditions to motor learning. Experiment 1 investigated the effect of visual guidance on the organization of bimanual coordination. Anti-phase 1:1 bimanual coordination was performed without (i) augmented information, (ii) under metronome pacing, and (iii) under visual guidance by a Lissajous plot. DFA analysis of temporal correlations revealed that the temporal dynamics of amplitudes and relative phase values deviated from the typical $1/f$ variation towards more random variation under visual guidance. Complexity of amplitudes, periods and relative phases, as measured by multiscale entropy, were also lowered in visual guidance. Experiment 2 investigated whether the weakening of temporal correlations and the loss of complexity under visual guidance have any role in learning. Specifically, the effects of practicing bimanual coordination at 90° of relative phase with constant visual guidance by a Lissajous plot, a fading schedule of guidance and no guidance were investigated. A control group that did not practice was included for comparison.

After practice, individuals were tested in independent execution (with no guidance) and under visual guidance. Results demonstrated better retention performance in the independent execution test after practice without visual guidance. Practice conditions did not affect temporal correlation of phases, amplitudes of periods at final tests. Complexity of amplitudes and periods showed some increase in the no guidance test for the group that practiced under constant visual guidance, but not for the other groups. A specificity of practice effect on complexity was found: performance in the visually guided test was associated with a general decrease in complexity for all groups (in agreement with Experiment 1), except for participants that practiced with constant visual guidance.

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CHAPTER ONE

Introduction

It is difficult to oscillate the two arms at different frequencies to generate polyrhythms (e.g., 3:2, 5:3) (e.g., Kelso & DeGuzman, 1988; Turvey, 1990; DeGuzman & Kelso, 1991; Treffner & Turvey, 1993), to oscillate limbs with one limb lagging a quarter of a cycle with respect to the other (Zanone & Kelso, 1992), or to draw shapes that differ in amplitude and/or direction simultaneously (Franz, Zelaznik, & McCabe, 1991). Execution of these movements requires extensive practice. Some coordination patterns, however, arise spontaneously and performance is naturally stable. It is easy to move segments in a common time frame (Kelso, 1995; Treffner & Turvey, 1993; Turvey, 1990). The preferential stability of 1:1 in-phase (0) and out-of-phase (180°) oscillations compared to any other phase relation also shapes spontaneous coordination (e.g. Kelso, 1984, 1995). Bilateral movements symmetric in relation to the midline of the body or in the same direction in external spatial coordinates are produced more easily than movements that are asymmetric or performed in opposite directions (e.g. Baldissera, Cavallari, & Civaschi, 1982; Jeka, Kelso, & Kiemel, 1993a, 1993b; Kelso & Jeka, 1992; Carson, Goodman, Kelso & Elliott, 1995; Swinnen, Jardin, Meulenbroek, Dounskaia, & Hofkens-Van Den Brandt, 1997). Moreover, in accommodating spatial differences of movements performed with the two hands, assimilation effects occur whereby the amplitudes and directions become more similar to each other (Ryu & Buchanan, 2004).

Spontaneous movement tendencies indicate that coordination is shaped by constraints that provide the basic organizational principles of movement. Research aimed at unraveling these constraints has commonly attributed foremost importance to motor factors. For example, the greater stability of the 0° (symmetric) compared to the180° (asymmetric) pattern has been attributed to the simultaneous activation of homologous as opposed to non-homologous muscle groups (Carson, Riek, Smethurst, Parraga, & Byblow, 2000; Kelso, 1984). Several studies confirm the role of muscular constraints in coordination (Carson et al., 2000; Salter, Wishart, Lee, & Simon, 2004; Temprado, Swinnen, Carson, Tourment, & Laurent, 2003). However, perceptual factors also play an essential role (Mechsner, Kerzel, Knoblich, & Prinz, 2001; Mechsner & Knoblich, 2004; Riek & Woolley, 2005). The typical differential stability between 0° and 180°, and the spontaneous phase transitions from 180° to 0° with increases in movement frequency (Kelso, 1984, 1995) are also present in perceptually coupled systems where a neuromuscular connection between components is absent (Kelso, DelColle, & Schöner, 1990). These phenomena have been demonstrated in unimanual coordination with visual and auditory signals (Bingham, 2004; Buekers, Bogaerts, Swinnen, & Helsen, 2000; Kelso et al., 1998; Wilson, Collins, & Bingham, 2005; Wimmers, Beek, & van Wieringen, 1992) as well as in interpersonal coordination tasks (Amazeen, Schmidt, & Turvey, 1995; Schmidt, Carello, & Turvey, 1990; Temprado et al., 2003). Moreover, evidence shows that visual and proprioceptive perception of phase are more accurate for 0°, followed by 180°, and least accurate for 90°, mirroring the main findings for stability of movement (Bingham, Schmidt, & Zaal, 1999; Bingham, Zaal, Shull, & Collins, 2001; Wilson, Bingham, & Craig, 2003). The suggested implication is that stable perceptual discrimination is intricately related to stable movement. In fact, individuals trained to visually discriminate 90° demonstrate improved performance producing hand movements at a 90° relation with a visual target without any motor training (Wilson, Snapp-Childs, & Bingham, 2010).

Current theory acknowledges that coordination arises from the mutual interplay of a variety of constraints acting on multiple levels of the perception-action system (Kelso, Fink, DeLaplain,

& Carson, 2001). These constraints can be manipulated to influence the stability and accuracy of coordination patterns (Park, Collins & Turvey, 2001, Temprado et al., 2003; Swinnen & Wenderoth, 2004; Riek & Wooley, 2005;Temprado, Salesse, & Summers, 2007). Especially interesting are demonstrations of a dramatic impact of simplified visual perceptual patterns on performance. For example, by associating a bimanual 4:3 rhythmic movement with a 1:1 visual feedback, 20 minutes of practice sufficed for successful execution (Mechsner et al., 2001). Alternatively, concurrent visual feedback of interlimb coordination by means of an angle-angle plot (i.e., a Lissajous figure) made difficult coordination patterns achievable: Individuals could produce 5:3 and 4:3 rhythmic movements after five minutes of practice, provided that metronomes were not used and limbs could not be seen (Kovacs, Buchanan, & Shea, 2010). These complex continuous movements had been previously considered impossible to perform without physical assistance (Summers, Davis, & Byblow, 2002). With these simple perceptual patterns, several phase relations other than 0° and 180° could also be consistently produced with reduced variability and error (Kovacs, Buchanan, & Shea, 2009a, 2009b).

The latter findings have been interpreted as instantiations of Prinz's common code/action-effect principles: To the extent that an intended action corresponds to a simple perceptually detected event, realization will be simplified (Mechsner et al., 2001; Prinz, 1997). The speculation is that voluntary movements are, in general, organized by way of a simple representation of the perceptual goals, whereas the corresponding motor activity, even if very complex, is spontaneously tuned in (Mechsner et al., 2001; Prinz, 1997). The suggestion thus is that appropriate harnessing of perceptual abilities and simplification of the perceptual goals can overrule basic constraints such that days of practice can be sidestepped. If the primary challenge in learning new motor patterns is the overcoming of basic coordination constraints (Zanone &

Kelso, 1992; Temprado & Swinnen, 2005), adequate task manipulations could become a formidable tool to aid learning and rehabilitation. However, being able to execute a coordination pattern under appropriately manipulated constraints within a few minutes does not necessarily imply that learning to execute the task in usual conditions will be facilitated (Kovacs & Shea, 2011). In fact there is evidence to suggest that execution under guidance of simplified feedback and free execution under usual perceptual circumstances might comprise two tasks that differ in significant ways.

Evidence for this line of thinking comes from a study reporting similarly remarkable results of task manipulations. As reviewed above, in bimanual movements the hands do not move independently. In an appropriately designed bimanual task, however, individuals were able to produce circle and square patterns simultaneously and to cycle their hands in different frequencies (3:4), performing as well as when producing congruent shapes (two circles or two squares) or cycling in the same frequency (1:1) (Rosenbaum, Dawson, & Challis, 2006). This indicates an exceptional degree of independence between hands. Individuals were, however, moving their two hands primarily in reactive fashion. Their task, suitably termed haptic tracking, was to maintain gentle physical contact with objects (without vision) in order to pursue them while they moved in the required patterns. Movements of the hands were thus guided by the objects. Arguably, the reason for the achieved degree of independence between hands was that the guided nature of the task obviated the involvement and contribution of levels of the perception-action system that engage in assembling maintaining self-control of an act (Rosenbaum et al., 2006). If this is the case, considering that coordination arises from a multitude of constraints from different levels of the system, constraints that are at play in guided and independently generated movements must differ considerably.

It is possible that movement guided by focused attention on simplified visual patterns may be similar to tracking tasks and might not have the same dynamical requirements of tasks performed independently under usual perceptual conditions. Thus, the interpretation that certain perceptual patterns are effective for simplifying the goal and thus the execution of the task, even if movement details remain equally complex (Prinz's principle) might be less than precise. In actuality, the use of simplified perceptual patterns might not just simplify the task goal but also introduce qualitative differences in the nature of the dynamical organization of movement details. Given the potential differences in dynamical organization of movement in tasks that require more of tracking and less of active involvement for self-controlled execution, the question arises as to whether guidance by simple perceptual patterns may facilitate acquisition of some aspects of coordinated movement while not furnishing enough opportunities to refine and stabilize others. In particular, training with reliance on guided versus independent execution may have distinct effects on the perceptual differentiation (perceptual learning) needed for the discovery and maintenance of new coordination patterns. The research proposed here thus had two goals: (1) assess potential differences in the dynamics of a coordination task executed under different perceptual conditions; (2) relate dynamical characteristics of execution under different perceptual conditions to changes that take place during learning, in particular, with respect to the dynamical organization of synergies and to perceptual refinement[1].

[1] See Appendix A for a brief report of a third experiment that had been planned to be part of this thesis but failed to yield satisfactory results and is thus not part of the main text.

CHAPTER TWO

Experiment 1: Addressing dynamical differences between coordination patterns executed under different perceptual conditions

Within the general motivation of investigating how perceptual manipulations could help overcome coordination constraints and affect learning, it is first necessary to explore how perceptual information affects coordination dynamics. The investigation of how guidance by simple visual patterns affects aspects of movement organization such as complexity and the structure of variability over time can help understand why conditions that may favor execution might not be useful for learning. This experiment focuses on the effect of visual guidance on the organization of movement synergies.

Functional levels of the action system

Bernstein thought of the movement system as a functional hierarchy in which each functional level solves a different class of motor problems (Bernstein, 1996; Turvey, 2007). In assembling an act, the levels of tone and synergy or muscular-articular links usually assume a background role of fulfilling the basic requirements for movement and the levels of space and action usually have leading roles in adjusting to environmental demands and planning movements according to task-specific goals. While the level of tone provides a basic state of preparedness for movement, it is the responsibility of the level of synergies to flexibly assemble and disassemble the necessary organizations of hundreds of muscles in an appropriate and timely fashion. In dynamic terms, this level is in charge of solving the degrees of freedom problem—the problem of how to compress the movement system's state space of very many dimensions into a control space of very few dimensions to achieve stable and reliable movement (Turvey, 1990; Turvey, 2007). For this purpose the level of synergies primarily exploits perceptual information from the haptic system. The haptic system is that by which one knows the body, and the objects adjacent to or attached to the body, by means of the body (Gibson, 1966). The intimate relation of the haptic system with movement organization at the level of synergies is made evident by the reported cases of neuropathy that turn standing walking, reaching or manipulating into tasks that are challenging if not impossible to perform without constant attention (Cole, 1995). An intact ability to perceive by muscle renders the level of synergy relative autonomy in guaranteeing internal coherence of large-scale patterning of muscle activity, irrespective of the intentions and meanings of movements. It is the duty of the levels of space and action to adjust to contextual demands and find a meaningful action solution for an environmental situation (Bernstein, 1996). For most tasks that require coordination with the environment, visual information plays a crucial regulatory role. At issue is how the superordinate requirements of adjusting movement to the visible spatio-temporal demands of a task are incorporated into the basic patterns produced by the level of synergies. More specifically, for the purposes of this thesis, the issue is whether execution of a movement coordination task under visual guidance can engender changes in the "architecture" of coordination and configure synergies with a qualitatively different dynamical organization. The concepts of state, parameter and graph dynamics provide useful language to frame this issue.

Dynamics levels in complex systems

Complex dynamical systems contain at least three types of dynamics: state, parameter and graph dynamics (Farmer, 1990; Saltzman & Munhall, 1992). State dynamics refers to the rules that directly govern the evolution of the system's variables, such as the position or velocity of a pendulum. Correspondingly, parameter dynamics governs changes in parameters such as, for example, damping or stiffness in a mechanical mass-spring system. Finally, graph dynamics refers to processes that govern changes in a system's dynamical architecture, which may involve changes in both the type and number of state variables and parameters. For example, a system of coupled oscillators that loses or gains oscillators exhibits graph dynamics (Saltzman & Munhall, 1992; Mitra, Riley, Schmidt, & Turvey, 1998).

Synergies have been characterized as complex dynamical systems or coordinative structures (Kugler, Kelso, & Turvey, 1980; Turvey 1990). A coordinative structure is defined as a temporarily assembled functional organization defined over a group of muscles and joints that converts the numerous underlying degrees of freedom into a task-specific, coherent low dimensional ensemble. In dynamical terms, synergies are emergent manifestations of dissipative dynamical systems that evolve into attractors. In so far as synergies are complex dynamical dissipative structures (Kugler, et al., 1980; Turvey 1990), both graph-dynamic specification of the synergy's architecture and the parameter-dynamic specification of the synergy's parameter set are necessary in assembling them (Saltzman & Munhall, 1992).

Perceptual guidance of movement and the architecture of coordination

In rhythmic coordination of two limbs or segments the state and parameter specification of 1:1 frequency locked pattern is captured by the extensively studied motion equation on the state variable ϕ, the difference in phase angles (relative phase) between oscillating segments (Haken, Kelso, & Bunz, 1985; Schöner, Haken, & Kelso, 1986):

$$\dot{\phi} = -a \sin\phi - 2b \sin 2\phi + \delta + \sqrt{Q}\,\xi_t \tag{1}$$

$\dot{\phi}$ is the first time derivative of ϕ, and the ratio of parameters b/a, shown to be related to the coupling between coordination components and to frequency of oscillation, determines the relative strength of the two intrinsically stable coordination modes, 0° (in-phase) and 180° (anti-phase). The δ term represents detuning due to a difference between the components, typically in terms of eigenfrequency (for other differences see Park & Turvey, 2008), with δ equal to zero when no such differences exist. The last term represents the effect of underlying noise processes generating variability in the coordination dynamics (for summaries on the development of this equation, see Kelso, 1995; Park & Turvey, 2008).

That vision can provide the informational support needed to establish the essential state dynamics as well as modulate parameter dynamics is evident from perceptually based coordination tasks (e.g., coordination with a visual display or with another person) and from the effects of vision on accuracy and stability of coordination reviewed in the Chapter 1. Further effects have been demonstrated when individuals had to visually attend to one hand while performing bimanual coordination. Visual attention to the hand renders the coupling between limbs asymmetric, with the direction of the asymmetry depending in part upon the attended hand (preferred or non-preferred). The magnitude of the asymmetry depends on coupled movement frequency (Amazeen, Amazeen, Treffner, & Turvey, 1996; Riley, Amazeen, Amazeen, Swinnen, Jardin, & Meulenbroek, 1996). These effects are expressed as changes in the parameter values, leaving however, the basic form of the elementary rhythmic synergy captured by the motion equation intact.

Effects on graph dynamics in turn would involve the introduction of different properties in the dynamics of coordination, with alterations in either number or type of component subsystems as well as the kind of coupling between these components. Changes in the number of components—changes in dimensionality—can be assessed by quantification of the number of active (dynamical) degrees of freedom (ADF), obtained with phase space reconstruction (Abarbanel, 1996). Formally, the number of ADF refers to the dimensionality of a given dynamics, the minimal number of first order autonomous differential equations needed to capture the time evolving dynamics of a system. The concept captures the dynamical variables brought into play during execution of a coordination pattern (for a tutorial see Mitra, Amazeen, & Turvey, 1998). Phase space reconstruction requires stationary time series for valid application. In this study, because very long time series were needed for reasons that will be apparent below, stationarity was unlikely and phase space reconstruction could not be reliably applied (see Appendix B for a report of limitations encountered). Instead, we focused on the complementary aspect of graph dynamics—the kind of coupling between component subsystems.

The coupling between degrees of freedom can be assessed with measures of the complexity. Although complexity has proved to be a slippery concept in all domains of inquiry, it has usually been assessed in studies on motor coordination with the quantification of nonlinear entropy (Newell, 1998; Vaillancourt & Newell, 2002; Vaillancourt, Slifkin, & Newell, 2002; Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009), a measure of the amount of information needed to predict the future state of the system. The entropy of a time series is thus a measure of its average uncertainty, or conversely, of the regularity or orderliness of a time series. Larger entropy values indicate less predictability and have been interpreted as reflections of more complex dynamics (Lipsitz & Goldberger, 1992).

A very important limitation of traditional entropy-based measures however, is the lack of straightforward correspondence between regularity and complexity. On the one hand, entropy increases with the degree of disorder and is maximal for completely irregular (random) systems. Intuitively, on the other hand, complexity is associated with "meaningful structural richness" which, in contrast to the outputs of random phenomena, exhibits relatively higher regularity, and would thus have lower entropy values than uncorrelated random signals. Completely random series are unpredictable but not intuitively understood as structurally "complex". Higher entropy values, therefore, may not always be associated with increased dynamical complexity (Costa, Goldberger, & Peng, 2002, 2005).

Recent explanatory proposals for the coordination of organisms and their environments draw on the recognition that complexity seen in behavior derives from the existence of numerous organismic substructures and subfunctions that are distributed over multiple spatiotemporal scales (Ihlen & Vereijken, 2010; Turvey, 2007). The tying together of several time scales in indefinitely nested loops allows for the stable and adaptable control which is characteristic of coordinated movement (Turvey, 2007; West & Griffin, 1998). A measure of the complexity of synergy organization should be able to capture this multi-scaled interdependence among components, processes, and their fluctuations. Because traditional entropy measures are restricted to a single scale, they fall short of this criterion. This intuition has instigated proposals for multiscale entropy measures, which look into the profile of regularity of a time series at several temporal scales. These multiscale measures are consistent with the intuitions of pattern complexity, as they consistently yield higher complexity values for simulated long-range correlated stochastic series (colored noise) compared to uncorrelated, unstructured random stochastic series (white noise) (Costa, Goldberger, & Peng, 2002). Multiscale entropy measures can thus reveal dynamic characteristics beyond those captured by dimensionality analyses, distinguishing between two high dimensional phenomena (colored or white noise) in terms of their structural richness—their complexity. Thus, while dimensionality measures refer to the number of causal factors—active degrees of freedom—interacting to produce a given output (can be indefinitely many for stochastic phenomena like random or correlated noise, few for low dimensional chaos, for example), measures of complexity may refer to the nature of interactions between these causal factors. They would act independently or in linear fashion for phenomena with low complexity (like random noise) and interdependently and nonlinearly for structurally complex phenomena (for correlated noise or deterministic chaos for example) (Dooley & Van de Ven, 1999). Complexity measures would thus allow for a characterization of changes in the “architecture” of the assembled synergy, that is, changes in the coupling aspect of graph dynamics under different perceptual circumstances.

Visual guidance in the form of Lissajous patterns (see Figure 1 for an example) allows individuals to produce a wide range of normally unstable coordinated movements with little training. Kovacs et al. (2009b), for example, demonstrated that Lissajous feedback eliminates the bistability that is the hallmark phenomenon of coordinated rhythmic movement (Kelso, 1995). Instead of two wells at the two stable coordination patterns (or one well at the one stable coordination pattern above a certain oscillation frequency) visual guidance appears to flatten out the landscape of possible coordination patterns. Such an effect is beyond that which can be produced by parametric changes (which is the transition from two attractors at 0° and 180° to one attractor at 0° to a ‘ghost attractor’ around 0°, Kelso, 1995; Park & Turvey, 2008). Instead, it is suggestive of a wider reorganization of coordination dynamics — it is suggestive of changes in the type and/or number of state variables and the parameters describing the coupling between them. Changes in the nature of the coupling would probably be evident at the level of graph dynamics with complexity analysis.

An additional window into the organization of the action system

A focus on movement variability over time may also reveal important aspects of the organization of degrees of freedom that underlies synergy formation (Riley & Turvey, 2002). Studies comparing independent execution, and execution guided by external temporal pacing or visual signals, offer further insight into how the adjustment of movement to external spatio-temporal demands of a task are incorporated into the basic patterns produced by the level of synergies. In self-paced voluntary movement, fluctuations in the time series of periods in finger tapping (Chen, Ding, & Kelso, 1997), locomotion (Hausdorff et al., 1996), hand oscillations (Delignieres, Lemoine, & Torre, 2004; Delignieres, Torre, & Lemoine, 2008), and in the time series of relative phase data in 0° and 180° bimanual coordination (Torre, Delignieres, & Lemoine, 2007) show an inverse relationship between power and frequency (1/*f* or pink noise). Pink noise, a kind of correlated noise, is indicative of a long-range memory process, in which a typical dependence in the series, for example a positive trend between successive values, appears nested with statistically similar trends expressed at larger scales (Diniz et al., 2010). Pink noise has been interpreted as a signature of interdependent interactions among the numerous components of a system, self-organization (the spontaneous organization that coordinates system behavior in the absence of a central controller) and emergence (the appearance of features that are not implicit in the parts of the system) (Van Orden, Holden, & Turvey, 2003; Turvey, 2007). Especially important for the purposes of the present work are speculations on the connections between 1/*f* noise and independent, self-controlled performance.

The typical 1/*f* structure observed over the series of periods in self-paced tapping disappears with metronome pacing. In its place, white or anti-persistent noise is observed (Chen et al., 1997; Torre & Delignieres, 2008). This finding is consistent with reduced complexity of metronomically paced gait as measured by multiscale entropy analysis (Costa, Peng, Goldberger, & Hausdorff, 2003). Similar changes towards more random variation are observed in oscillation periods of individual hands coordinating at 0° under metronome guidance (Torre & Delignieres, 2008). These findings have been interpreted as reflections of enhanced sources of external constraint reducing voluntary control (Van Orden et al., 2003; Kloos & Van Orden, 2010; Van Orden, Kloos, & Wallot, 2011). The presence of external guidance would cede control to the environment via entrainment with auditory or visual information, resulting in whitened (closer to random), less pink pattern of variation. If it is the case that guided execution obviates the involvement of levels of the action system normally engaged in producing voluntary, independently executed movement (Rosenbaum et al., 2006), the execution of a bimanual coordination pattern under visual guidance should manifest changes away from $1/f$ and towards whiter variation. These changes of underlying dynamics should appear in spite of possible similarities at the level of overall pattern accuracy and stability.

If deviations from $1/f$ towards whiter noise are confirmed, they would indicate that entrainment to the metronome or reliance on the Lissajous plot supplements or substitutes for mechanisms that are at play during independent execution and interferes with the intrinsic (pink noise) dynamics of purposeful coordination. Consequently, fluctuations in the data series increasingly come to reflect errors in matching the guiding signal (Van Orden et al., 2003). Additionally, changes in the direction of less correlated variation can indicate less integration of components of the underlying synergy, with acquisition of degrees of freedom that begin to vary with greater independence (Kiefer, Riley, Shockley, Villard, & Van Orden, 2009), a finding that would be also captured by lower values of complexity. In this study, analyses of correlational structure and complexity were used to evaluate these expectations.

Modifying the dynamics of antiphase

When performed freely or in accompaniment with a metronome, antiphase coordination of two limbs is less precise (e.g., larger absolute error) and more variable (e.g., larger standard deviation) than in-phase coordination. It has been reported that when the two coordinations are performed in accompaniment with a corresponding 1:1 Lissajous plot, the aforementioned antiphase versus in-phase differences are substantially reduced (see Figure 2 in Kovacs et al., 2009b). Given the well-established attractor dynamics of in- and anti-phase (with in-phase the more attractive state, e.g., Kelso, 1995) the question arises as to the specific changes in antiphase coordination dynamics induced by a guiding antiphase Lissajous plot. Experiment 1 was directed at identifying these specific changes. It did so through the analyses of correlational structure and complexity.[2]

Performance of the anti-phase pattern was tested in three perceptual conditions: independent execution (IE), metronome pacing (MP) and visual guidance by a Lissajous plot (VG). The participants were divided into two groups. In Group A they performed the coordination in all three conditions with the frequency that was freely selected in IE. In Group B the MP frequency was that of IE, with VG frequency freely chosen. The Group A versus Group B contrast provided an assessment of the influence of the frequency requirement on VG.

Method

Participants

Thirty undergraduate students (15 in Group A and 15 in Group B) volunteered to participate in partial fulfillment of a course requirement. All participants classified themselves as right-handed. None had neuromuscular conditions affecting perception-action or previous experience with the task. The experimental protocol was approved by the Institutional Review Board of the

[2] The most striking effects of visual guidance by the simplified pattern of Lissajous plots are demonstrated for patterns not spontaneously available, such as 90° out of phase. Thus, the 90° pattern would be a good candidate to reveal potential effects of the Lissajous on the underlying dynamics. However, the dramatic effects on accuracy and stability for untrained individuals performing the pattern with and without the Lissajous (Kovacs et al., 2009a) could introduce important confounds in the results. Changes in the underlying dynamics could be present, nevertheless, even for the naturally stable 180°, with confounds related to accuracy and stability avoided.

University of Connecticut. All participants provided informed consent.

Materials

Figure 1 depicts the experimental device built for Experiment 1. It consisted of two vertical handles attached to optical encoders (AutomationDirect TRD-SH2500-VD, with a resolution of 2500 counts per revolution). The axis of the handles allowed movement to happen around the wrists in flexion and extension in the transverse plane. The participants sat in front of the device with arms aligned parallel to each other and to the floor and supported in a custom-made armchair. A screen prohibited vision of the hands and wrists. A computer monitor used for VG, and a speaker used for MP, were placed in front of participants. Hand position data was recorded at 200Hz.

Procedure

Assignment of participants to Groups A and B was determined by order of appearance at the laboratory. Each participant was run separately in a single experimental session. Upon arrival, participants received general information about the research topic and gave verbal agreement for participation. They sat in front of the device and were instructed to grasp its handles and move them rhythmically together, leftward and rightward in the horizontal plane. They were told to choose a movement speed and movement amplitude that felt comfortable, and to keep them as consistent as possible. All participants performed two trials of anti-phase coordination between left and right hands in each of three perceptual conditions: IE, MP and VG, with IE trials first, followed by MP trials, and VG trials last.

For both groups, IE consisted of performing the anti-phase coordination at a freely chosen pace and amplitude. Online monitoring of movement provided the experimenter with an estimate of the individual participant's preferred frequency. This frequency dictated the length of time needed to complete a minimum of 270 cycles (approximately 5 to 9 min depending on individual frequency). Delignieres and colleagues (Delignieres et al., 2006) have suggested that 256-512 data points are the minimum necessary for estimating the structure of noise in a time series. The mean frequency used in the two IE trials dictated the metronome pace for the MP condition. Participants in both groups were told to synchronize hand cycles with the sound cycles. A continuous sound metronome with tone oscillation instead of discrete beats was used to avoid induction of “anchoring,” a local stabilization of the cycle near the discrete pacing signal (Byblow, Carson, & Goodman, 1994; Torre, Balasubramaniam, & Delignières, 2010) thus allowing for better comparability between the other two conditions that involved no discrete perceptual anchors.

The shape of a Lissajous plot represents relative phase while its size represents amplitude. For example, a circle corresponds to a relative phase of 90° and its diameter establishes amplitude. The Lissajous plot used in VG was a diagonal line on the computer monitor representing perfect anti-phase and established a reference for performance (Figure 1). A dot represented the conjugate movement of the right and left hands. Participants were instructed to move the handles of the device so that the dot would match the general shape and size of the line. They were given five minutes to practice using the visual guidance (Kovacs et al., 2009a, 2010) before data collection begun. For participants of Group A, the metronome was turned on for the final 2.5 minutes of practice time to remind them of the IE and MP frequency they should attempt to replicate in the two VG trials. The metronome was used only during the pre-trials practice time, to avoid confounding effects of visual and temporal guidance, and especially because the use of metronomes (as well as the sight of hands) hinders the facilitation effects of Lissajous on movement production (Kovacs et al., 2009a, 2010). Participants in Group B also practiced for the 5 minutes before the two VG trials, but without any frequency requirement (the metronome was not turned on). They were allowed to choose the frequency that felt most comfortable and were instructed to keep it as constant as possible throughout the two trials.

Data reduction

The experiment was run with a custom-made Simulink model that received data from the encoders. Displacement data were imported into Matlab for analysis. A time derivative of each displacement series was generated. For that purpose, the displacement series were filtered with a low-pass Butterworth filter with a cut-off frequency of 5 Hz. The derivative series were later filtered with a cut-off frequency of 10 Hz. A peak-picking algorithm was used to define four kinds of events in a cycle (Figure 2): maximum wrist flexion (corresponding to peaks in the displacement series), maximum wrist extension (valleys in the displacement series), the inflexion point between maximum flexion and maximum extension (valleys in the derivative speed series), and the inflexion point between peak extension and peak flexion (peaks in the derivative speed series).

The use of four events per cycle allowed for longer event series to be used in the analyses of temporal correlations and complexity. The events were used for calculations of cycle amplitudes, periods, and discrete relative phase. Discrete relative phase was defined as:

$$\phi_i = \left(\frac{t_{i+1} - \tau_{i+1}}{t_{i+1} - t_i}\right)360 \tag{2}$$

where t_i and t_{i+1} represent the timings of two successive events (of the same kind, as defined above) in the dominant hand, and τ_{i+1} the timing of the corresponding event in the opposite hand.

Several methods are available for the analysis of the structure of temporal variability in a time series. Commonly used methods include Detrended Fluctuation Analysis (DFA) (Peng, Mietus, Hausdorff, Havlin, Stanley, & Goldberger, 1993; Peng, Havlin, Stanley, & Goldberger, 1995), Power Spectral Density analysis (PSD) (Eke, Herman, Bassingthwaighte, Raymond, Percival, & Cannon et al., 2000), Rescaled Range Analysis (Hurst, Black, & Simaika, 1965), Dispersional Analysis (Bassingthwaighte, 1988) and Maximum Likelihood Estimation (Deriche & Tewfik, 1993). Choice between these methods needs consideration of the possible kinds of stochastic phenomena.

One family of stochastic processes is called fractional Brownian motions, in which successive increments in the series are correlated, meaning that a given trend in the series is likely to be followed by a similar trend (positive correlation) or an opposite trend (negative correlation) in the future. Differentiation of a fractional Brownian motion series produces another class of stochastic processes called fractional Gaussian noise. These two classes of processes have different properties: fractional Brownian motion is non-stationary with time-dependent variance, while fractional Gaussian noise is a stationary process with a constant expected mean value and constant variance over time. Because of the different properties of these processes, the methods of estimation of the strength of temporal correlations they present are necessarily different (Delignieres et al., 2006).

While Rescaled Range Analysis, Dispersional Analysis and Maximum Likelihood Estimation are appropriate to only one of the two classes of stochastic phenomena, DFA and PSD are insensitive to the dichotomy. Because the expectation in this work was to find variation close to pink noise, which is defined at the boundary between fractional Gaussian noise and fractional Brownian motion, we chose to use DFA and a modified version of PSD to analyze the correlational properties of the series of periods, amplitudes and phases.

DFA assesses the strength of temporal correlations in a time series (Peng et al., 1993, 1995). It does so by analyzing the relationship between the mean magnitude of fluctuations in the series and the length of the intervals over which these fluctuations are determined. Typically, fluctuations will increase with interval length. For series with temporal correlation, fluctuations scale as a power-law with window lengths. To determine whether that is the case, the time series is first integrated and subdivided into non-overlapping intervals of equal length. In each interval, the local trend—the locally best-fit regression line—is subtracted. Next, the root-mean-square of the locally detrended time series is computed for each interval of the same length. The process is repeated over increasing interval lengths up to the limits of the series length. If fluctuations scale as a power law with interval length, a linear relationship will be evident in a double log graph. The slope of the line relating fluctuation size to interval length is the scaling exponent α, the result of DFA. In a process where the value at one step is completely uncorrelated with any previous values, that is, there is no temporal correlation (white noise), $\alpha = 0.5$. The temporal correlation of pink noise (1/*f* noise) is characterized by $\alpha = 1$. Therefore, variation in a time series gets closer to the structure of pure white (Gaussian) noise as the scaling exponent approaches 0.5 and closer to pure pink noise as the scaling exponent approaches 1. For fractional Gaussian noise $0 < \alpha < 1$ and for fractional Brownian motion $1 < \alpha < 2$.

In the present study, DFA with linear detrending was performed on interval sizes varying from a minimum size of 16 to a maximum size shorter than or equal to series length divided by 4. A customized Matlab routine was used to calculate DFA (based on Ihlen, 2012). To ascertain that the log-log relation was linear (a requisite for a meaningful interpretation of α) the coefficient of the regression of log fluctuation size on log interval length had to be greater than

0.95. Additionally, a regression with a quadratic term should not be significantly better than a linear regression according to a chi-square test on deviance statistics. DFA results that did not pass both these criteria were not used in statistical analyses.

A modified version of PSD was also used to add consistency to the results. While DFA works on the time domain, PSD works on the frequency domain, on the basis of the periodogram obtained by the Fast Fourier Transform algorithm. The scaling exponent β is estimated by calculating the negative slope ($-\beta$) of the line relating log squared-amplitude (power) to log frequency. For Gaussian (white) noise $\beta = 0$. The temporal correlation of pink noise ($1/f$ noise) is characterized by $\beta = 1$. For fractional Gaussian noise $-1 < \beta < 1$ and for fractional Brownian motion $1 < \beta < 3$. α and β are interconvertible, with $\alpha = (\beta+1)/2$ within the range of fractional Gaussian noise and $\alpha = (\beta-1)/2 + 1$ within the range of fractional Brownian motion.

The modified version of PSD involves three pre-processing operations performed before Fourier transformation. First, the mean of the series is subtracted from each value, then a parabolic window is applied to the series, and thirdly the resulting series is linearly detrended. Finally, the fitting of β excludes the high-frequency power estimates ($f > 1/8$ of maximal frequency). This modified version has been shown to provide more reliable estimates of the spectral index β and was designated as lowPSDwe by Eke et al. (2000). As in DFA, obtaining a well-defined linear fit in the log-log plot is a requisite for the indication of long-range correlation in the original series[3]. The deviance statistics criterion used for DFA was also used for lowPSDwe. A function developed for R (downloaded from http://www.psychologie.uni-

[3]The presence of a linear relationship between log power and log frequency in PSD is necessary but not sufficient for claiming that long range correlations that characterize $1/f$ noise are present in the series, as the linear relation can also be generated by processes that are short-range dependent. Wagenmakers et al. (2004) proposed ARFIMA/ARMA modeling to evaluate the statistical evidence for long-range correlations. For the series of periods and phases in bimanual coordination, Torre and Delignières have shown that such models confirm long-range correlations and validate the use of scaling exponent estimation methods.

heidelberg.de/projekte/zeitreihen/R_Code_Data_Files.html) was used for data processing (Stadnitski, 2012; Stroe-Kunold, Stadnytska, Werner, & Braun, 2009).

Complexity was characterized with Multivariate Multiscale Entropy (Multivariate MSE) after Multivariate Empirical Mode Decomposition (MEMD) (Ahmed, Li, Cao, & Mandic, 2011; Ahmed & Mandic, 2011; Ahmed, Rehman, Looney, Rutkowski, & Mandic, 2012). See Appendix C for a review of available methods and a rationale for choosing MEMD-enhanced Multivariate MSE. The method is based on the calculation of Sample Entropy, which measures the negative logarithm of the conditional probability that two sequences that are similar for m points remain similar at the next point, within a tolerance r (Richman & Moorman, 2000). The multivariate version of Sample Entropy (Ahmed & Mandic, 2011, 2012) is based on multivariate embedded reconstruction with composite delay vectors, with a typical time lag $t=1$. It enables entropy calculations for multivariate time series data, taking into account both within and cross-series dependencies. As is usual in the literature, m was set to 2 and r was set to $0.15 \times$ the standard deviation of the standardized time series. Standardization—transformation to z-scores—was used prior to Multivariate Sample Entropy calculation to allow for a similar threshold criterion across all time series. Previous studies indicated good statistical reproducibility for the univariate Sample Entropy with these parameter values (Costa et al., 2007; Richman & Moorman, 2000).

In MEMD-enhanced Multivariate MSE, Multivariate Sample Entropy is calculated over multiple oscillatory scales defined by the intrinsic mode functions extracted with MEMD (Amoud, Snoussi, Hewson, Doussot, & Duchêne, 2007; Hu & Liang, 2012), the multivariate version of Empirical Mode Decomposition (EMD). The latter is a data driven method specifically developed for decomposing nonlinear, non-stationary signals into their intrinsic frequency components (Huang et al., 1998; Rilling, Flandrin, & Gonçalvés, 2003). The successive components obtained with EMD are called intrinsic mode functions. Different intrinsic mode functions capture the properties of the original signal on different time scales. The first extracted intrinsic mode function is the highest frequency component in a signal containing plenty of detail. The subsequent intrinsic mode functions are narrowband and monocomponent, with the characteristic frequency decreasing with the intrinsic mode function number. The last intrinsic mode function is the overall trend (see Figure 24 in Appendix B for an illustration). Even if the original signal is non-stationary, the intrinsic mode functions are much better conditioned and are typically quasi-stationary (Ahmed et al., 2012). MEMD is capable of simultaneous decomposing two (Rilling, Flandrin, Gonçalvés, & Lilly 2007), three or more time series (Rehman & Mandic, 2010) into intrinsic mode functions. The advantage of using MEMD is its mode alignment property. The intrinsic mode functions generated for each series of the multivariate series set are same in number and belong to the same frequency band, making their comparison meaningful (Ahmed et al., 2012).

The extracted intrinsic mode functions are used to generate multiple intrinsic data scales. The present study followed procedures delineated by Hu and Liang (2012) and defined coarse-to-fine scales by the cumulative sums of sequential intrinsic mode functions. To define coarse-to-fine scales, the sum of all intrinsic mode functions, all but the last one, all but the last two, all but the last three and so on were taken. This way the first scale contains the full original signal and the last contains the intrinsic mode function of higher frequency content (Hu & Liang, 2012). Sample Entropy and its multivariate version are inappropriate for nonstationary signals, but because intrinsic mode functions are narrow-band quasi-stationary signals, Multivariate Sample Entropy can be calculated for the scales defined with intrinsic mode functions.

Applying the methods of analyses to participants' data

For each participant, time series were used to compose multivariate sets that were decomposed with MEMD. Series of relative phases measured four times a cycle were used to assemble multivariate set with 6 series (two trials in each of three conditions: IE, MP and VG), Series of right and left hand amplitudes measured four times a cycle were used to assemble multivariate sets with 12 series (series of each hand for the two trials in the three conditions). Likewise, series of periods measured four times a cycle were used to assemble a multivariate set with 12 series. The number of data points *N* of all series ranged from 348 to 2677. Given that maximum number of intrinsic mode functions is equal to $\log_2(N)$ (Costa et al, 2007)—8.4429 to 11.38 for the analyzed series—the outputs of MEMD were used to define 8 coarse-to-fine scales fully aligned between conditions for each participant to allow for comparisons. Multivariate Sample Entropy was then used to calculate entropy of all scales defined for the bivariate (right and left hand) series of amplitudes and periods, and Sample Entropy was used to calculate entropy of all scales defined for the univariate series of relative phases.

Performance was also characterized with traditional and circular statistical measures. Accuracy was quantified by taking the circular mean of relative phase over time within each trial. Stability was quantified by taking the circular standard deviation of relative phase over time within each trial. Movement pace was quantified by taking the mean of half cycle periods (in seconds) over time within each trial. All measures were averaged between the first and second IE, first and second MP, and first and second VG for each participant for improved reliability of estimates (Torre & Delignieres, 2008; Torre et al., 2007).

Results

Task performance

To characterize task performance across conditions and groups, accuracy was compared with a 2 (Group) × 3 (Condition) mixed ANOVA. No significant effects were found, indicating that participants of both groups were able to maintain similar phase relations between the hands across experimental conditions, with an overall mean of 177.66 (±6.21). The ANOVA on mean stability, however, showed a significant effect of Condition, $F(1.169, 32.727) = 37.75$, $p < 0.001$ after the Huynh-Feldt (H-F) correction for violation of sphericity[4]. Pre-planned repeated contrasts showed that, contrary to previous studies (Kovacs et al., 2009a, b), stability was lower for VG compared to MP, $F(1, 28) = 32.10$, $p < 0.001$, and to IE, $F(1, 28) = 49.77$, $p < 0.001$. Stability of MP and IE were not significantly different.

Effects of instructions regarding movement pace were also captured by the ANOVA. Both Condition, $F(1.041, 29.136) = 11.43$, $p = 0.002$, and the Condition × Group interaction, $F(1.041, 29.136)$, $= 6.375$, $p = 0.016$, were significant for pace. While pace was not different across conditions for Group A, $F(1.007, 14.093) = 1.30$, $p = 0.274$, in Group B conditions differed in pace, given that participants were free to chose the pace for VG performance, $F(1.090, 14.045) = 10.18$, $p = 0.006$. Movement pace was significantly lower for VG compared to MP, $F(1, 14) = 10.36$, $p = 0.007$, and for VG compared to IE, $F(1, 14) = 10.00$, $p = 0.007$, in Group B. Accuracy, stability and pace values averaged across participants are shown in Table 1.

Temporal correlations

Relative phase

A 2 (Group) × 3 (Condition) mixed ANOVA was used to examine the effects of experimental manipulations on the structure of temporal variability. For DFA's α and lowPSDwe's β exponents for the time series of phases, ANOVAs revealed a significant effect of

[4] Hereafter, note that non-integer degrees of freedom indicate that the H-F correction was applied.

Condition, $F(1.643, 46.00) = 36.61$, $p < 0.001$ for α and, $F(2, 36) = 10.13$, $p < 0.001$ for β. Neither Group nor the interaction between Group and Condition were significant for α or β ($p >$ 0.098), indicating similar results for Group A and Group B. Repeated contrasts showed that α and β were significantly lower for VG compared to MP, $F(1, 28) = 50.83$, $p < 0.001$, and $F(1, 18) = 14.73$, $p = 0.001$, respectively, and VG compared to IE, $F(1, 28) = 30.06$, $p < 0.001$, and $F(1, 18) = 10.27$, $p = 0.005$, indicating weaker temporal correlations and variability closer to white noise in VG. The α for IE was significantly lower than for MP, $F(1, 28) = 7.26$, $p = 0.012$, but β was not significantly different between these two conditions ($p = 0.395$). These results are summarized in Figure 3. Descriptive statistics are available in Table 2.

Amplitudes

For the series of amplitudes, the ANOVA on α values was significant for Condition, $F(1.373, 37.083) = 52.96$, $p = 0.001$. The α value was lower for VG compared to MP, $F(1, 27) = 62.45$, $p < 0.001$, and VG compared to IE, $F(1, 27) = 53.19$, $p < 0.001$, with no difference between the α for IE and the α for MP ($p = 0.246$). The effect of Group was not significant ($p = 0.172$), but the interaction between Condition and Group was, $F(1.373, 37.083) = 9.50$, $p = 0.002$. Post hoc tests indicated that, according to the interaction, α did not differ between Group A and B for IE or MP ($p > 0.324$), but was significantly lower for VG in Group B compared to Group A, $t(27) = 3.04$, $p = 0.005$. The ANOVA on β values showed a significant effect of Condition, $F(2, 46) = 28.36$, $p < 0.001$. The interaction between Condition and Group was not significant ($p = 0.255$), but Group was, $F(1, 23) = 4.51$, $p = 0.045$, indicating lower β for Group B compared to Group A. These results are summarized in Figure 4. Descriptive statistics are available in Table 3.

Periods

For the series of periods, the ANOVA showed that Condition was significant for ⍰, F(1.536, 41.461) = 35.38, $p < 0.001$, and β, $F(2, 22) = 6.33$, $p = 0.007$. Repeated contrasts showed that while ⍰ and β values did not differ significantly between IE and VG ($p > 0.328$), they were significantly lower for MP compared to VG, $F(1, 27) = 42.03$, $p < 0.001$, $F(1,11) = 5.07$, $p = 0.046$, respectively, and to IE, $F(1, 27) = 38.38$, $p < 0.001$, $F(1,11) = 11.02$, $p = 0.007$, respectively. Groups and the Condition × Group interaction were not significant for either ⍰ or β values ($p > 0.276$). These results are depicted in Figure 5. Descriptive statistics are available in Table 4.

Complexity

Relative Phases

A 2 (Group) × 3 (Condition) × 8(Scale) mixed ANOVA detected a significant main effect for Condition, $F(2, 56) = 57.57$, $p < 0.001$). Pre-planned contrasts indicated that averaged over Group and Scale, VG had significantly lower complexity values compared to MP, $F(1,28) = 85.76$, $p < 0.001$, and to IE, $F(1, 28) = 78.36$, p < 0.001. MP and IE did not differ, $F < 1$. The effect of Group was also significant, $F(1, 28) = 4.32$, $p = 0.048$. Across conditions and scales, entropy values were uniformly lower for Group A compared to Group B. However, because differences were uniform and there were no significant interactions involving Group ($p > 0.261$) separate ANOVAs per group were not used. These results are summarized in Figure 6. Descriptive statistics are available in Table 5.

Amplitudes

The 2 (Group) × 3 (Condition) × 9 (Scale) Mixed ANOVA indicated a significant effect of Condition, $F(1.463, 40.96) = 31.80$, $p < 0.001$. Pre-planned contrasts showed that VG had significantly lower values compared to MP, $F(1, 28) = 36.19$, $p < 0.001$, and IE, $F(1, 28) = 34.91$, $p < 0.001$. MP and IE did not differ, $F < 1$. The Condition × Scale interaction was significant, $F(4.933, 138.130) = 4.91$, $p < 0.001$, indicating that differences across scales, irrespective of group, were different between conditions. The Group × Scale interaction was also significant, $F(8, 232) = 4.77$, $p = 0.015$, indicating that the differences across scales, irrespective of Condition, was different between groups. Because differences between scales were not of interest, these interactions were not investigated further. Neither the effect of Group nor any other interactions involving Group were significant therefore separate analysis per group was not conducted. These results are summarized in Figure 7. Descriptive statistics are available in Table 6.

Periods

The 2 (Group) × 3 (Condition) × 8 (Scale) mixed ANOVA identified a significant main effect of Conditions, $F(1.180, 33.048) = 32.97$, $p < 0.001$. Pre-planned contrasts indicated that VG had significantly lower values compared to MP, $F(1, 28) = 38.38$, $p < 0.001$) and to IE, $F(1, 28) = 29.92$, $p < 0.001$. MP had significantly higher values than IE, $F(1, 28) = 5.24$, $p = 0.03$. The Condition × Scale interaction was significant, $F(5.520, 154.556) = 3.32$, $p = 0.005$, indicating that differences across scales, irrespective of group, were different between conditions. Because differences between scales were not of interest, these interactions were not investigated further. Neither the effect of Group nor any other interactions involving Group were significant; therefore separate analysis per group was not conducted. These results are summarized in Figure 8. Descriptive statistics are available in Table 7.

Summary of Results

Performance: Overall, performance as characterized by mean phase was similar between groups and conditions. Contrary to expectations however, the standard deviation of phase was higher for VG performance compared to the other conditions. Instructions were effective:

Periods were similar across conditions in Group A, while in Group B they were longer for VG performance.

Temporal Correlations: The structure of temporal variability for the series of phases deviates from that typical of $1/f$ in the direction of white noise under VG. The correlational structure of amplitudes also deviates in the same direction. These effects on amplitudes were more pronounced in participants of Group B, who performed the task at a freely chosen slower pace in the VG condition. For the series of periods, the deviation towards whiter variation happened only for the MP condition. Overall, DFA and lowPSDwe results were consistent with each other.

Complexity: Entropy values were consistently lower for VG compared to the other conditions for all the series (the sequences of phases, amplitudes and periods) on the time scales defined from the original series to the finer (higher frequency) scales of variation, in both groups. These results indicate a consistent effect of VG in reducing complexity. Complexity for phases was uniformly lower for Group A compared to Group B. For the series of periods, MP had higher complexity than IE.

Discussion

Experiment 1 was designed to investigate possible dynamical differences between coordination patterns executed under different perceptual conditions. Specifically, the intent was to investigate the impact of visual guidance on synergy organization. It was expected that movement execution under guidance of simplified visual feedback and free execution would comprise two tasks that differ in significant ways in terms of the underlying movement synergy organization. Measures of complexity were used to assess possible changes in synergy organization at the level of graph dynamics. Measures of correlational structure were used to assess how the reliance on environmental information interferes with the typical dynamics of purposeful coordination for independent, self-controlled movement execution.

Before considering the results of these measures, it is necessary to point out that the stabilizing effect of Lissajous guidance was not reproduced in this study. Participants of both groups produced the anti-phase pattern equally well in terms of accuracy (gauged by mean relative phase across conditions) but stability (gauged by variability around the mean pattern) was lower for VG compared to the other conditions across groups. Kovacs et al. (2009b) tested performance of bilateral elbow flexion and extension movements with Lissajous guidance for seven relative phase patterns varying from 0° to180° in steps of 30°, and found a significant reduction in variability of phase for all patterns except 0°, in comparison to performance with visual metronomes. In the present study, it might have been the case that the requirement to coordinate flexion and extension of wrist movements according to the visual template of perfect 180° induced heightened awareness of small deviations from the ideal movement, leading participants to persistent attempts of increasingly precise corrections and thus an increase in phase variability (Schmidt & Bjork, 1992). It is known that handedness affects bimanual coordination, leading to a phase shift with a small lead of the dominant hand (Treffner & Turvey, 1996). Individuals are usually unaware of this shift. It its possible that in previous studies the resolution of the visual displays used was within or below this small shift while in the present study a finer resolution of the display allowed for finer discrimination of small deviations. The absence of a stabilizing effect of VG, however, did not preclude manifestations of the visual guidance on underlying synergy organization, as was detected by changes in temporal correlations indices and complexity measures. Moreover, temporal correlation indices and complexity measures for VG were not related to stability of relative phase (as measured by the Pearson correlation coefficient, $p > 0.085$). The frequency requirement, however, did affect dynamical measures, as the whitening seen for the series of amplitudes under VG was more pronounced in participants of Group B, who performed the task at a self-chosen pace[5].

In the present experiment, multiscale entropy measures successfully discriminated the complexity of series of phases, amplitudes and periods generated under VG, MP and IE. It is important to note that for the series of periods, DFA and lowPSDwe indicated that MP induced more random temporal variation over time. This seems inconsistent with complexity results for the series of periods indicating higher complexity in MP compared with IE. However, it may also indicate that DFA and MEMD-enhanced Multivariate MSE pick out different features of the dynamics. (A low correlation between DFA and Multiscale Entropy (MSE) indicate that the two methods are not closely related, cf. Costa et al. (2003). No studies comparing DFA and MEMD-enhanced Multivariate MSE could be found.). More importantly, however, is the fact that while DFA and lowPSDwe were used to analyze the series of right hand periods (and amplitudes) only, MEMD-enhanced Multivariate MSE enables entropy calculation for multivariate time series data and is suited to detect both within and cross-series dependencies. Therefore, while DFA as used here speaks only to the temporal correlations of the series of periods (and amplitudes) of the right hand, MEMD-enhanced Multivariate MSE speaks to the dependencies across the series of periods (and amplitudes) of the right and left hands. MEMD-enhanced Multivariate MSE therefore captures aspects of the temporal (and spatial) coordination between hands.

Interestingly, it has been shown that 1/*f*-like temporal correlations are absent from the series of stride intervals in metronomic conditions but present in the series of asynchronies to the metronome (Delignieres & Torre, 2009). These findings counter the conclusions of Hausdorff et

[5] Frequency apparently did not affect complexity, as no Groups × Conditions interactions were significant. The overall lower complexity of relative phases seen for Group A compared to Group B may have been due to individual variation and sampling effects.

al. (1996), who suggested that the intervention of attentional and intentional processes focused on external pacing induced a kind of "oversimplification" of the system, extinguishing long-range correlation in stride interval series. The presence of long-range correlations in the series of asynchronies suggests that the intrinsic complexity of the system is still at work in metronomic conditions, but is expressed differently in overt performance (Delignieres & Torre, 2009). Note that the series of asynchronies is the mathematical integration of the series of periods (Chen et al., 1997). Whether the measure of complexity used in the present study can capture, in the multivariate series of periods, this hidden face of complexity is a question for further study.

For VG, results indicated lower complexity in all scales for the series of phases, amplitudes and periods. Thus, Lissajous guidance, providing spatial information specific to amplitude and relative phase, has broad effects on coordination complexity. Results of DFA and lowPSDwe, which refer to unimanual hand dynamics, are specific to the nature of guidance, as only the series of periods were whitened under MP, and only under MP, while only the series of amplitudes and phases were whitened under VG, and only under VG. Note that for MP, unimanual temporal dynamics is whitened but cross-hand temporal dynamics increases in complexity, while for VG, unimanual spatial dynamics is whitened but cross-hand spatial dynamics decreases in complexity. It could have been the case that if VG was informative only about amplitude (just as MP is specific only to timing) but not to phase, then the same pattern of results observed for temporal dynamics could have been observed, that is, increased cross-hand spatial complexity could have been observed. However, the simplified information about relative phase is supposed, by its nature, to affect coordination between hands, and between-hand coordination in a rhythmic 1:1 task is necessarily manifested both in the spatial and temporal cross-hand dynamics. Information about phase from the Lissajous plot is, therefore, information about cross-hand amplitude and cross-hand temporal relations. It is information about unimanual amplitude, and it whitens unimanual amplitude series. It is not information about unimanual timing, and it does not whiten unimanual period series. But it does affect complexity of both cross-hand amplitude and cross-hand temporal relations. That the effect of relative phase guidance on coordination complexity is distinct (leading to lower complexity) to that found for guidance of exclusively temporal nature (and speculatively for guidance of exclusively spatial nature, which does not lead to lower complexity) is an interesting finding.

How should the findings of generalized lower complexity for VG be interpreted? If complexity measures do capture the nature of the coupling between component subsystems in synergy organization, lower complexity levels would indicate that the active degrees of freedom begin to vary with less concinnity and greater independence. As to the functional implications of these changes, lower complexity has been associated with pathological states and ageing (loss of complexity hypothesis, Lipsitz & Goldberger, 1992), while higher complexity has been associated with healthy, skillful behavior (Newell & Vaillancourt, 2001). Many of the studies that investigated these associations have assessed complexity with measures of dimensionality (e.g., correlation dimension, Newell, 1998; Newell, Broderick, Deutsch, & Slifkin, 2003; Newell, Gao, & Sprague, 1995; Newell & Vaillancourt, 2001) and single scale approximate or sample entropy (Kaplan et al., 1991; Newell, 1998; Newell, 2002; Newell et al., 2003; Vaillancourt & Newell, 2003). The risks of computing dimensionality measures have already been pointed out (see Appendix A), and single-scale entropy measures have been shown to produce inappropriate results with regards to complexity. Moreover, studies showing that learning and ageing can involve either increase or decrease in complexity of motor behavior have led to a dismissal of the association between of ageing and loss of complexity as well as between learning and increased complexity as a universal principles (Newell & Vaillancourt, 2001; Vaillancourt & Newell, 2002). To anticipate, Experiment 2 investigates whether the loss of complexity in synergy organization under visual guidance has any role in learning.

The correlational structure of movements was altered by visual guidance. Results indicated whiter variation of amplitudes and phases. Whitening is to be expected for the series of periods in metronome pacing, due to the mathematical relationship between the correlational properties of a series and of its differenced or integrated counterparts. If periods in synchronization were still 1/*f* noise, asynchronies would be highly nonstationary, given that the series of asynchronies is the mathematical integration of the series of periods and that the integration of 1/*f* is nonstationary, persistent fractional Brownian motion. This result would be inconsistent with the stable nature of synchronized performance (Torre, Balasubramaniam, & Delignières, 2010). The whitening of temporal correlations under pacing or external guidance more generally, however, has been interpreted as more than just a mathematical expectation. In fact, whitening of spectra takes place for different perturbations to the intrinsic fluctuations of independent execution, and these perturbations are not easily reconciled with differentiation and integration relationships. After-trial accuracy feedback decreases the long-range correlation structure of time estimates (Kuznetsov & Wallot, 2011), and randomization of intertrial intervals has the same effect (Van Orden et al., 2003). Likewise, times for simple response or word-naming tasks (Van Orden et al., 2003) which include a response cue at each trial show less clear signals of 1/*f* noise compared to tasks that do not involve response cues (Diniz et al., 2010). Finally, the series of asynchronies for syncopated tapping show clearer signs of 1/*f* noise compared to synchronized tapping, in which performance is required to closely match external signals. Together, these results indicate that 1/*f* noise changes in predictable ways across tasks as a function of external constraints and support a broad association between 1/*f* noise and the intrinsic dynamics of independent, self-controlled performance (Van Orden et al., 2003). External guidance appears to cede control to the environment and disrupt the 1/*f*-like structure, resulting in a whitened temporal correlation profile (Diniz et al., 2010). The changes in correlational structure away from 1/*f* observed for phases and amplitudes in continuous visual guidance also support the interpretation of 1/*f* structure as a signature of self-controlled performance[6]. Present results suggest, however, that change in temporal correlation seem to be specific to the nature of execution constraints, and does not relate to a general "oversimplification" of the system (Hausdorff et al., 1996). Complexity might be just a system finding a way to expresses itself differently in overt performance.

Yet, if the intrinsic dynamics of healthy, skillful self-controlled behavior is typically long-range correlated as in 1/*f* noise (Kloos & Van Orden, 2010; Van Orden, Kloos, & Wallot, 2011), the disruption of this structure caused by visual external guidance might influence the course of learning. The use of visual guidance in training a new coordination pattern may simplify the coordination goal and make it quickly achievable, but due to its effect on synergy complexity and variability structure, it might nevertheless not supply favorable conditions for the refinement necessary for independent performance. These speculations will be tested in Experiment 2.

[6] Possibly, the more intense whitening of the amplitude series seen in Group B is related to a greater possibility to entrain with external guidance given the self-chosen pace for task performance.

CHAPTER THREE

Experiment 2. Dynamical and perceptual changes with practice under different task constraints

It has been argued that the use of a visual pattern like a Lissajous plot can simplify the goal and, in consequence, the execution of an interlimb coordination task (Kovacs et al., 2009a, 2009b, 2010, Kovacs & Shea, 2011). The results of Experiment 1 suggest, however, that any simplification of the task goal, and any attendant enhancement of performance, is accompanied by changes in the organization of movement details that may render task performance less dexterous. Visual guidance with phase-specific information introduces qualitative differences in the nature of the dynamical organization of movement, changing its complexity and temporal correlations.

Given the differences in dynamical organization of movement executed under guidance, the question arises as to whether practice guided by simple perceptual patterns may facilitate acquisition of some aspects of coordinated movement while not furnishing enough opportunities to refine and stabilize others. Experiment 2 investigated whether the loss of complexity and the weakening of temporal correlations in synergy organization under visual guidance have consequences for learning.

Coordination learning and perceptual ability

The early phase of coordination learning is characterized by discovery of the relevant collective variable (Amazeen, 1996; Mitra et al., 1998). In the case of bimanual rhythmic coordination, the relevant collective variable is relative phase. Bingham and colleagues (Bingham et al., 1999, 2001; Zaal, et al., 2000) have suggested that the initial difficulty in performing a 90° pattern has been linked with the inherently noisy perception of this phase relation. In a series of experiments, participants were asked to judge visual displays of dots moving at some mean relative phase (that could vary from 0° to 180° in steps of 30°) subject to varying frequency and amounts of variability (added noise). On average, judgments of mean relative phase were accurate, but the variability of these judgments varied in the manner expected from the dynamics of the stochastic version of the Haken-Kelso-Bunz equation (Equation 1): Judgments were less variable at 0°, maximally variable at 90° and had intermediate variability at 180°. When participants were asked to judge phase variability itself, these results were replicated: 0° was judged to be maximally stable, 180° stable but less so, and 90° maximally unstable even with no added noise. When phase variability was explicitly added, this was only clearly discriminated at 0°, somewhat discriminated at 180°, and not discriminated at all at 90°. These results were later replicated for haptic perception of relative phase (Wilson, Bingham, & Craig, 2003). These findings support the idea that the ability to perceptually resolve phase and phase variability play an important role in the stability of movement patterns (Bingham, 2004). They suggest that stable perception allows for stable movement. This prediction was confirmed by evidence that training individuals to visually discriminate variability around 90° led to improved performance in coordinating hand movements with a visual target at 90°, without any training in the movement task (Wilson et al., 2010). In terms of the dynamical HKB model, the ability to easily discriminate 0° and 180° supports the existence of attractors at these particular phase relations, and the development of perceptual differentiation of other phase relations is probably intrinsic to the attractor-forging process that allows the stable performance of new coordination patterns.

In the aforementioned circumstances, the efficacy of visual guidance by Lissajous plots lies in low dimensional spatiotemporal information about the two limbs and, thus, their relative phase. Drawing on Bernstein's intuitions about functional levels of the movement system, this external source of information may engage Bernstein's level of space more easily (Turvey, 2007). In Bernstein's scheme, each level solves a particular class of problems, with the level of space being most articulated in finding an action solution for an environmental situation (Bernstein, 1996). The Lissajous plot may thus provide the level of space with a shortcut to the location and global geometry of the attractor to be established and stabilized during learning.

However, there is a need to distinguish the attractor associated with an action subsystem and the particular means by which that attractor is realized. Finding the basic geometry of attractors and achieving fluent and efficient motions on those attractors can be separate matters. The latter is based on the degree of attunement to local, muscular-articular information specific to the attractor (Kugler & Turvey, 1987). This reasoning is consistent with the idea that attractor location and attractor strength are factorized according to visual-spatial (Bernstein's level of space) and muscular-proprioceptive constraints (Bernstein's level of synergies), respectively (Park, Collins, & Turvey, 2001; Temprado et al., 2003; Temprado et al., 2007). It also suggests that, in spite of possible shortcuts that the level of space might capitalize on to discover attractor location and geometry, the standardization and stabilization of the skill, the subsequent phase of learning (Mitra et al., 1998), necessitates a deeper involvement of Bernstein's synergy level and its haptic informational support (Turvey, 2007). Of crucial importance in this standardization and stabilization phase are opportunities for differentiation of haptic perception during practice.

Coordination learning and perceptual guidance

A traditional hypothesis in motor learning regarding the role of augmented feedback in learning is the *guidance hypothesis* (Salmoni, Schmidt, & Walter, 1984). It suggests that the provision of too frequent external feedback about the movement (either of its outcome or pattern) may make the use of inherent sources of feedback superfluous, which then leads to the failure to learn error detection capabilities necessary for performance of the task. More specifically, frequent feedback is assumed to prevent learners from focusing on their own movements, which is seen as a precondition for the development of an effective movement representation. Supposedly, if the external feedback presented to the learner becomes incorporated into the movement representation, performance becomes dependent on the feedback and is disrupted when this feedback is withdrawn (Salmoni et al., 1984; Schmidt, 1991). Support for the detrimental role of frequent feedback on retention of practiced movements comes from several studies showing that practice in conditions with less frequent and less immediate feedback or with less guidance during movement, though more detrimental for performance, is more beneficial for the learning of motor skills than practice in conditions where feedback is provided following every trial, with little post-response delay or where guidance is constantly provided (e.g., Maslovat, Brunke, Chua, & Franks, 2009; Park, Shea, & Wright, 2000; Salmoni et al., 1984; Schmidt & Wulf, 1997; Vander Linden, Cauraugh, & Greene, 1993; Winstein, Pohl, & Lewthwaite, 1994; Winstein & Schmidt, 1990). Irrespective of the plausibility of internal models qua elements of the explanation of guidance effects, evidence from Experiment 1 indicates that practice with and without guidance implicates qualitative differences in the nature of the dynamical organization of movement, with changes in its complexity and temporal correlations. Measurable changes in dynamics might be related to the potential of practice under different perceptual constraints to help individuals learn to perform the target coordination pattern independently.

If guidance by externally provided information in fact impedes the use of intrinsic information sources, practice under constant visual guidance should have a detrimental effect on haptic perceptual refinement. Visual guidance can yield accurate performance of new coordination patterns (Kovacs et al., 2009a) while allowing the individual to cede control to the environment; it thus may bypass the need to refine the detection of the haptic information necessary to support performance without visual guidance. Additionally, if refined haptic perception is supportive of stable movement coordination, and visual guidance is conductive to accurate performance (in line with the factorization of attractor strength and attractor location to the levels of synergies and space, respectively), practice under constant visual guidance might lead to less stable performance, notwithstanding adequate accuracy.

Coordination learning and changes in complexity and temporal correlations

Bernstein (1996) describes the general problem of coordination as the mastery of redundant biomechanical degrees of freedom within a kinematic chain of movement. The solution to this problem is essentially the role of level of synergies (Turvey, 2007). In a dynamics inspired interpretation, the problem of degrees of freedom is the problem of how to compress a state space of very many dimensions into a control space of very few dimensions. The solution lies not in prohibiting biomechanical degrees of freedom but in reducing the number of variables arising in these linked biomechanical degrees of freedom that must be controlled independently. Said differently, the solution lies in reducing the number of ADFs. The acquisition of a new motor skill is therefore viewed as a change from high-dimensional control to low-dimensional control (Mitra et al., 1998; Turvey, 2007).

The number of active dimensions (or active degrees of freedom) of behavior that can be regulated independently has been taken as a signature feature of complexity (Newell & Vaillancourt, 2001; Vaillancourt & Newell, 2002), with the acquisition of dimensions indicating increased complexity. There is conflicting evidence regarding direction of change in dimensionality during learning. Pioneer studies by Mitra et al. (1998) showed a reduction in the number of active degrees of freedom (ADFs) during the acquisition of a bimanual coordination at 90° of relative phase. Other studies by Newell and collaborators using different tasks and measures have shown either decreases or increases in dimension (see Newell & Vaillancourt, 2001 for a review).

In Experiment 2, dimensionality is dissociated from complexity. As anticipated in Experiment 1, complexity measures are likely to capture an aspect of dynamics that is complementary to dimensionality, namely, the kind of coupling between component subsystems. Dimensionality measures do not seem to be appropriate proxies for complexity due to the fact that equally high dimensional phenomena, such as white and colored noise, are not recognized as equally complex. Colored noise is thought of as having greater structural richness and thus greater complexity compared to white noise. Likewise, low dimensional chaotic dynamics can be recognized as more complex than high dimensional white noise. In the present view, it is more appropriate to allow that complexity may refer not to the number of independent dimensions interacting to produce dynamics, but to the nature of interactions between these active degrees of freedom. Thus the change in complexity can take place orthogonally to the change in dimensionality. What should be expected with regards to change in complexity during learning?

Lower complexity levels would indicate that the active degrees of freedom begin to vary with less concinnity and greater independence. One could suppose therefore that lower complexity could be associated with more variable and less stable performance, typical of early stages of learning, and that learning should proceed with an increase in complexity. Stability of bimanual coordination is typically indexed by the standard deviation of relative phase values. In effect, in Experiment 1, lower complexity values for the series of phases were observed in the visual guidance condition, which also produced lower stability. Nevertheless, the relationship between complexity and magnitude of variability (statistical dispersion) is not straightforward. Because complexity is assessed by the overall behavior of entropy measures across different scales, the correlational properties of a time series influence its complexity. Moreover, in multiscale entropy calculations the series are standardized so that the entropy values assigned to two different time series are not just a trivial consequence of differences between their variances but result from different organizational structures. It is known that both series with higher variability and those that are more random tend to be more entropic. In general, therefore, the actual entropy values result from a complex combination of dispersion and correlational structure (Costa et al., 2005). Although some studies have made a link between higher complexity (as measured by approximate or sample entropy) and better performance (e.g., Newell & Vaillancourt, 2001; Newell, Vaillancourt & Sosnoff, 2006; Vaillancourt & Newell, 2002), the link is based on single scale entropy measures that do not correspond to the general understanding of complexity. Experiment 2 investigates if and how complexity, as measured by multiscale entropy measures, changes after practice with and without visual guidance.

As far as a stronger temporal correlational structure relates to higher complexity, there is some evidence supporting the speculation of an increase in complexity with learning. Wijnants et al. (2009) have reported improvement in performance in a precision aiming task during learning associated with an increase in the strength of temporal correlations in the sequence of movement durations, that is, with a change towards 1/*f* variation. If the intrinsic dynamics of skillful self-controlled behavior is typically long-range correlated and complex as in 1/*f* noise (Kloos & Van Orden, 2010; Van Orden et al., 2009), the disruption of this structure caused by external guidance might negatively influence the course of learning. The use of visual guidance in training a new coordination pattern may simplify the coordination goal and make it quickly achievable, but due to its effects in synergy organization, namely a decrease in complexity and a weakening of temporal correlations, it might nevertheless hamper the development of the complex, $1/f$-like dynamical organization typical of independent skillful performance. Experiment 2 tests these speculations.

Method

Participants

Forty-four undergraduate students participated in the experiment. All participants classified themselves as right-handed. None had neuromuscular conditions affecting perception or action. Three participants had taken part in Experiment 1, but had no experience in performing the phase relation of 90°. The experimental protocol was approved by the Institutional Review Board for ethics in research of the University of Connecticut, and volunteers received financial compensation of $50.00 to participate in five 1-hour experimental sessions.

Materials

The same device used in Experiment 1 for the movement coordination task was used in Experiment 2. No auditory feedback equipment was used. Hand position data was recorded at 200 Hz. For the assessment haptic of perceptual ability, a specially designed apparatus was used to produce several phase relationships between two vertically oriented levers that were to be tracked with nonvisible, flexions-extensions of the wrists. Events in the cycles of movement of the levers (e.g. reversal points) were not audibly distinguishable. The apparatus consisted of two discs that could be connected with each other at different points (Figure 9). Given the point of connection, the rotation of the superior disc by the experimenter would move the two vertical levers on the horizontal plane at nine phase relations: 0°, 22.5°, 45°, 67.5°, 90°, 112,5°, 135°, 157.5° and 180°.

In all assessment and practice sessions, a screen was used to cover hands and wrists. A computer monitor was used to provide visual feedback of performance.

Procedure

Assignment of participants to groups was determined by order of appearance at the laboratory. Each participant was run separately in either two sessions or five sessions. Two sessions “defined” the control group (CTRL). Five sessions “defined” the experimental groups: the constant visual guidance group (CVG), the fading visual guidance group (FVG), and the no visual guidance group (NVG).

Upon arrival, participants received general information about the research topic and gave verbal agreement for participation. They were informed about the schedule of the study, which consisted of two one-hour sessions spaced three days apart for CTRL or five experimental sessions on consecutive weekdays for CVG, FVG and NVG. The first and last sessions for CVG, FVG and NVG were dedicated to a perceptual assessment and a movement assessment. The three intervening sessions were dedicated to movement practice.

Assessment of haptic perception of relative phase. The apparatus shown in Figure 9 was hidden from the participant’s view by a curtain. The participant grasped the occluded vertical handles under the instructions that (a) the handles would be moved by the experimenter, and (b) the participant’s task was to follow (actively) the movement of the handles with their hands, flexing and extending their wrists as necessary, without pushing or pulling the handles. When the movement stopped, the participant was instructed to use the computer mouse to mark a point on a continuous visual scale on the screen that was labeled “hands moving exactly opposite” at one extreme and “hands moving exactly together” at the other extreme (representing muscularly in-phase and anti-phase coordination respectively). The middle of the scale was marked with the expression “in-between.” The experimenter demonstrated each phase relation once, exemplifying where the scale would be marked for each phase relation, using the order 0°, 180°, 90°, 22.5°, 45°, 67.5°, 157.5°, 135°, and 112.5°. Then these phase relations were repeated each once more in the same order and the participant was asked to verbally indicate where he or she would have marked the visual scale, to make sure instructions had been clearly understood. For the actual task, five trials of 10 cycles for each of the nine phase relations were performed in a random order, with the same random order for all participants. The experimenter used an earphone with a metronome signal at 1Hz to standardize movement frequency in all trials. This assessment of haptic perception of relative phase (HPRP) was given in the first and last sessions and referred to as HPRP-pre and HPRP-post.

Assessment of intermanual coordination of 90° relative phase. Participants were given two movement trials using the apparatus depicted in Figure 1, without any visual guidance (computer screen turned off). The two trials were approximately eight minutes in duration. They were as long as needed to obtain sufficient data points, e.g., a minimum of 256 for DFA. Participants were instructed to choose a speed and size of movement that felt comfortable and to try to keep both as constant as possible throughout the duration of movement. They were instructed to move the handles so that they would never be moving exactly in the same direction and never exactly in opposite directions, but in a pattern that was in between these two possibilities, so that one handle would always be half-way ahead of the other (90° out of phase). Participants watched a two minutes video with the top view of a person using the apparatus to perform the task. Participants had three minutes to get acquainted with the equipment and find a comfortable speed and size of movement that they felt could be kept constant before data recording begun. Hands were not visible in any of the movement trials. Following the terminology of Experiment 1, this assessment was designated Independent Execution (IE). Like HPRP it was given prior to the first and subsequent to the last practice sessions and referred to, respectively, as IE-pre and IE-post.

The three experimental groups. As prefaced above, the three experimental groups were distinguished by the visual guidance regime of the practice sessions. CVG performed all practice trials throughout the experiment with the guidance of a Lissajous plot (a circle representing the 90° phase template, with a dot that corresponded to movement of the levers). FVG performed the task with progressively shorter times of visual guidance, starting with 90s and decreasing by 5.29 s after each block of four trials so that the last four trials on the last practice session were performed with no visual guidance at all. After the preset time, the dot would disappear from the screen. NVG performed all practice trials without visual guidance. Of the 44 participants enrolled in the study, seven completed only the first assessment session and their data is not reported here. Of the remaining, eight were in CTRL, eleven in NVG, nine in CVG and nine in FVG.

Before the beginning of the first practice trial, participants received specific instructions about their task. For CVG and FVG, participants were told that there would be a plot of a circle on the computer screen in front of them. A dot would also be visible. The dot would move on the screen according to how they moved the device's handles. Their task was to move them so as to make the dot go around the circle, matching its general shape and size and keeping a consistent rhythm. FVG participants were told that the dot would disappear after some time, and they had to do their best to keep moving in the same pattern after that happened. NVG participants received the same instructions used in IE-pre and a demonstration given by the experimenter. Participants of all groups performed three blocks of eight practice trials per session. After each block, they were shown a plot of their movement trajectory in the immediately preceding trial, in angle-angle coordinates. They were told that the closer the plot was to a definite circle the better would have been their performance. They were also told that their objective was to get as close as they could to a perfect circle by the end of the practice sessions, and that their performance would be assessed on the last day, when they would be asked to perform the movement without any feedback (IE-post).

Roster of pre- and post-assessments. To reiterate, for all groups, haptic perception of relative phase (HPRP) and Independent Execution (IE) tests preceded the first practice session and followed the third practice session. Additionally, for all groups, on the last session, IE-post was followed by a further assessment of movement, namely, two trials with guidance from a Lissajous plot of 90°. This assessment was designated Visual Guidance (VG). For CTRL and NVG participants, who had no experience with Lissajous guidance, instructions were the same as used on the first day of practice by CVG and FVG. CTRL and NVG participants had 5 minutes to become acquainted with the Lissajous guidance before the VG test trials began (Kovacs et al., 2009a, 2010). In sum, pre-practice tests were HPRP and IE; post-practice tests were HPRP, IE, and VG.

Data Reduction

For the haptic perceptual task, HPRP, measures of standard deviation, root mean square error and absolute error were used to characterize performance. Standard and circular statistical measures were used to characterize amplitudes, periods, and phases produced in the movement assessment and practice trials. DFA was used to quantify the strength of temporal correlations present in movement assessment trials. Because in Experiment 1 the results of ${}^{low}PSD_{we}$ replicated the results of DFA, ${}^{low}PSD_{we}$ was not used here. MEMD-enhanced Multivariate MSE was used to quantify complexity from coarse-to-fine scales of the series of amplitudes, periods and phases. Intrinsic mode functions used for complexity analysis were defined for each multivariate set composed of data from the 6 assessment trials (two in IE-pre, two in IE-post and two in VG) to take advantage of mode alignment and favor comparability. Thus the multivariate set had 12 components for amplitudes and periods (from right and left hands) and 6 components for relative phase. In order to define the same number of scales to all series, we considered 8 scales, which corresponded to the maximum number of scales definable for the shortest series.

Results

Longitudinal Change

Figures 10 to 12 illustrate the changes in accuracy, stability and the composite of accuracy and stability from IE-pre assessment, throughout the practice trials to the final IE-post and VG assessments.

Motor Performance

Accuracy in producing target relative phase. A 3 (Assessment) × 2 (Trial) × 4 (Group) mixed ANOVA on relative phases averaged over each trial for each participant showed no effects of trial or of any interaction involving trial. The effect of Assessment (IE-pre versus IE-post versus VG) was significant, $F(2, 66) = 44.78$, $p < 0.001$. Inspection of individual values in the IE-pre indicated that all participants performed with mean relative phases at 90° or higher (means and standard deviation values are available in Table 8). Repeated contrasts showed that relative phase was significantly lower and closer to 90° in IE-post, $F(1, 33) = 25.94$, $p < 0.001$, and significantly lower and closer to 90° in VG, $F(1, 33) = 21.37$, $p < 0.001$. The Assessment × Group interaction was significant, $F(6, 66) = 2.84$, $p = 0.016$.

Repeated measures ANOVAs for each group and one-way ANOVAs comparing mean phase between groups at each assessment were used to investigate the Assessment × Group interaction. No differences were found between groups in IE-pre. Bonferroni-corrected tests showed that there was no change in the CTRL from IE-pre to IE-post, while all the other groups showed improvement in accuracy ($p < 0.011$). Due to the high intra-group variability in the post-practice IE-post, however, post hoc tests with Bonferroni correction indicated that only the NVG performed significantly better than the CTRL ($p = 0.03$). There were no other differences between groups. Compared to IE-pre, all groups performed with significantly better accuracy in VG ($p < 0.006$), but compared to IE-post, Lissajous improved accuracy only for the CTRL ($p = 0.017$). Groups did not differ in VG. Results are illustrated in Figure 13.

Stability of produced relative phase. A 3 (Assessment) × 2 (Trial) × 4 (Group) mixed ANOVA on the SD of relative phases over each trial for each participant showed no effects of trial or of any interaction involving trial. The effect of Assessment (IE-pre versus IE-post versus VG) was significant, $F(2, 66) = 9.48$, $p < 0.001$. Repeated contrasts showed that SD of relative phase averaged across all participants was significantly lower in IE-post compared to IE-pre, $F(1, 33) = 12.67$, $p = 0.001$). IE-post and VG did not differ, $F < 1$. The Assessment × Group interaction was significant, $F(6, 66) = 3.19$, $p = 0.008$.

Repeated measures ANOVAs for each group and one-way ANOVAs comparing stability between groups at each of IE-pre, IE-post, and VG were used to investigate the interaction. No differences between groups were found for IE-pre. There were no significant changes across IE-pre, IE-post, and VG for either group CTRL or group FVG. Bonferroni-corrected tests showed that IE-post was superior to IE-pre for groups CVG and NVG ($p < 0.02$). Groups were not different from each other, however, in IE-post.

When VG was compared to IE-pre, only group CVG showed significantly improved performance ($p = 0.008$). Compared to IE-post, group NVG had a significant decrease in stability in the VG assessment ($p = 0.034$). When groups were compared on VG, CTRL had significantly higher SD compared to CVG and FVG ($p < 0.004$), which were not different from each other ($p > 0.999$). Group NVG did not differ from CTRL ($p > 0.999$) and was marginally different from the other two groups ($p = 0.057$). Results are illustrated in Figure 14.

Composite accuracy and stability around target relative phase. The circular version of root mean square error (RMSE) around 90° was used to characterize performance. A 3 (Assessment) × 2 (Trial) × 4 (Group) mixed ANOVA on RMSE over each trial for each participant showed interactions involving Trial. The main effect of Trial was significant, $F(1, 33) = 4.25$, $p = 0.047$. RMSE averaged over all second trials was significantly lower than RMSE averaged over all first trials. The effect of assessment was significant, $F(2 ,66) = 47.13$, $p < 0.001$. Repeated contrasts showed that RMSE of relative phase averaged across all participants was significantly lower for IE-post than IE-pre, $F(1, 33) = 50.54$, $p < 0.001$. In turn, RMSE of VG was significantly lower than RMSE of IE-post (F (1, 33) = 6.953, p = 0.013). Additionally, Assessment × Group was significant, $F(6, 66) = 5.22$, $p < 0.001$.

Repeated measures ANOVAs for each group and one-way ANOVAs comparing RMSE between groups at each assessment were used to investigate the interaction. No differences between groups were found for IE-pre, and CTRL was unchanged from IE-pre to IE-post. All the other groups showed significant improvements from IE-pre to IE-post ($p < 0.020$). For IE-post, post hoc tests with Bonferroni correction indicated, however, that only group NVG performed significantly better than CTRL ($p = 0.020$). There were no other differences between groups. The three experimental groups performed significantly better ($p < 0.016$) in the comparison of VG to IE-pre. In respect to IE-post, however, only VG affected group NVG and did so detrimentally (p

< 0.030). In respect to VG, groups CVG and FVG were not different from each other, and both had significantly lower RMSE compared to NVG and CTRL ($p < 0.015$), which were also not different from each other. The results are illustrated in Figure 15.

Haptic Perceptual Performance

Absolute error, RMSE and standard deviation of perceptual judgments. A 2 (Assessment) × 9 (Angle) × 4 (Group) mixed ANOVA on absolute error values showed marginally significant effects for HPRP (post versus pre), $F(1, 31) = 3.91$, $p = 0.057$, and the HPRP × Angle interaction, $F(6.55, 203.114) = 1.88$, $p = 0.081$. Group was not significant, $F < 1$. Means and SD of absolute errors by assessment and angle are available in Table 9 and illustrated in Figure 16.

For RMSE values, HPRP × Angle interaction was significant, $F(6.205, 192.344) = 2.31$, $p = 0.034$, with Assessment (post versus pre) only marginally so, $F(1, 31) = 3.24$, $p = 0.082$. To investigate interactions, differences between HPRP-post and HPRP-pre were tested for each of three angles: 67.5°, 90°, and 112.5° (angles at which we expected most important changes due to learning) with paired t tests and Bonferroni-corrected α values (0.5/3 = 0.016). There was a significant reduction in RMSE from HPRP-pre to HPRP-post for 90° ($p = 0.012$) and 112.5° ($p = 0.015$). (It needs to be emphasized, however, that neither Group, nor the interaction of Group with Angle, was significant.) Means and SD of RMSE for HPRP-pre and HPRP-post and for angle are available in Table 9 and illustrated in Figure 17.

The standard deviation of HPRP showed a marginally significant difference from HPRP-pre to HPRP-post, $F(1, 31) = 3.11$, $p = 0.088$) and a marginally significant Angle × Assessment interaction, $F(7.288, 225.914) = 1.985$, $p = 0.055$. Means and SD of standard deviation of judgments by assessment and angle are available in Table 9 and illustrated in Figure 18.

Temporal correlations

Relative Phases. A 3 (Assessment) × 2 (Trial) × 4 (Group) mixed ANOVA on the α of DFA for the series of phases showed a significant effect of assessment, $F(2, 52) = 20.17$, $p < 0.001$. Repeated contrasts showed that α was significantly lower for VG than IE-pre and IE-post, $F(1, 26) = 32.132$, $p < 0.001$. Neither Group nor any other effect was significant. These results are illustrated in Figure 19. Descriptive statistics are available in Table 10.

Amplitudes. The 3 (Assessment) × 2 (Trial) × 4 (Group) mixed ANOVA on DFA's α for the series of amplitudes showed a significant effect of assessment, $F(2, 56) = 35.78$, $p < 0.001$). Repeated contrasts showed that α for IE-pre and IE-post did not differ, $F < 1$. The magnitude of α was significantly lower for VG than IE pre-practice and IE post-practice, $F(1, 26) = 54.42$, $p < 0.001$. A significant Group × Assessment interaction was also found. To investigate the interaction, one-way ANOVAs comparing α between groups at each assessment were used. No differences between groups were found for IE-pre and IE-post, $F(3, 33) = 1.59$, $p > 0.21$. In VG, groups were significantly different, $F(3, 32) = 11.03$, $p < 0.001$. CVG had significantly lower α compared to all the other three groups ($p < 0.009$). FVG, NVG and CTRL were not different from each other ($p > 0.577$). These results are illustrated in Figure 20. Descriptive statistics are available in Table 11.

Periods. The 3 (Assessments) × 2 (Trials) × 4 (Group) mixed ANOVA on DFA's α for the series of periods showed a significant effect only for Trial, $F(1, 22) = 4.79$, $p = 0.039$). Averaged across groups and assessments, α was modestly but significantly lower for the second trial Descriptive statistics are available in Table 12.

Complexity

Phases. A 3 (Assessment) × 2 (Trial) × 4 (Group) × 8 (Scale) mixed ANOVA on entropy values of the series of phases over coarse-to-fine scales showed that neither trial nor any interaction involving trial were significant. The Assessment × Scale × Group interaction was significant, $F(18.772, 206.493) = 2.00$, $p = 0.010$. To investigate interactions, separate 3 (Assessment) × 8 (Scale) ANOVAs were conducted for each group to determine how each group changed across IE-pre, IE-post and VG.

When each group was analyzed separately, only the control group showed an Assessment × Scale interaction, $F(7.328, 51.293) = 3.28$, $p = 0.005$. However, ANOVAs comparing the 3 (Assessment) entropy values per scale for the control group showed no significant differences.[7] These results are illustrated in Figure 21. Descriptive statistics are available in Table 13.

Amplitudes. A 3 (Assessment) × 2 (Trial) × 4 (Group) × 8 (Scale) mixed ANOVA on entropy values of the series of amplitudes showed a significant Assessment × Trial × Scale × Group interaction, $F(25.198, 277.183) = 1.55$, $p = 0.049$. Further analysis did not investigate the effect of trial but instead focused on Group and Assessment related changes at the analyzed scales. To investigate interactions, separate 3 (Assessment) × 8 (Scale) ANOVAs were conducted for each group to determine how each group changed across IE-pre, IE-post and VG.

CTRL showed a significant effect of Assessment, $F(2, 14) = 9.25$, $p = 0.003$) and Scale × Assessment interaction, $F(6.297, 44.081) = 3.80$, $p = 0.003$. Post hoc tests indicated that for CTRL there was no change in overall complexity values from IE-pre to IE-post but there was a significant reduction from IE-post to VG ($p = 0.013$). The interaction indicated that differences were significant for all scales ($p < 0.021$) except the last. For NVG the effect of assessment was not significant, but the Scale × Assessment interaction was, $F(7.428, 74.283) = 2.24$, $p = 0.037$).

[7] Relative phase is a circular variable. Unintentional coordination errors, very common in performing a pattern such as 90°, introduce significant amounts of circular variation in mean relative phase series. That variation could compromise calculations used in DFA and complexity measures (which are all based on linear statistics) leading to increased variability in estimates. Qualitatively, however, changes in complexity of relative phase are similar to those observed for amplitudes and periods, in line with results of Experiment 1. The non-significance of the observed changes might be due to influences of circularity in estimation procedures.

ANOVAs comparing the 3 (Assessment) entropy values per scale for NVG however did not show any significant differences at any scale ($p > 0.101$). For FVG, overall complexity values increased in IE-post and decreased in VG, but the effect of Assessment was only marginally significant, $F(2, 16) = 3.48$, $p = 0.056$). For CVG, there was a significant effect of assessment, $F(2, 16) = 8.79$, $p = 0.003$), overall complexity values increased significantly from IE-pre to IE-post, while the change from IE-post to VG was not significant. These results are illustrated in Figure 22. Descriptive statistics are available in Table 14.

Periods. A 3 (Assessment) × 2 (Trial) × 4 (Group) × 8 (Scale) mixed ANOVA on entropy values of the series of phases over coarse-to-fine scales showed that neither trial nor any interaction involving trial were significant. The Assessment × Scale × Group interaction was significant, $F(9.683, 106.510) = 2.604$, $p = 0.008$. To investigate interactions, we ran separate 3 (Assessment) × 8 (Scale) ANOVAs for each group to how each group changed between assessments.

ANOVAs showed that CTRL had a significant Assessment effect, $F(2, 14) = 38.33$, $p < 0.001$. Bonferroni-corrected post-hoc tests showed that for CTRL there was no difference between IE-pre and IE-post. Complexity however was significantly lower for VG compared to IE-post ($p = 0.001$). The Scale × Assessment interaction was also significant for CTRL, $F(3.598, 25.185 = 12.64$, $p < 0.001$. ANOVAS at each scale showed significant differences between assessments for all scales ($p < 0.005$) except the last. NVG also showed both a significant Assessment effect, $F(2, 20) = 11.80$, $p < 0.001$) and a significant Assessment × Scale interaction, $F(2.869, 28.692) = 3.25$, $p = 0.038$. Post hoc comparisons between assessments showed that complexity for VG was significantly lower than for IE-post ($p < 0.001$) but not for IE-pre ($p = 0.226$). ANOVAs comparing assessments for NVG at each scale showed significant differences between assessments for all scales ($p < 0.007$) except the last. FVG had a significant Assessment × Scale interaction, $F(4.346, 34.767) = 5.91$, $p = 0001$. ANOVAs at each scale showed significant differences between assessments for the first to fourth scales ($p < 0.034$), with complexity for VG at those scales lower than for IE-post ($p < 0.043$) and no different from IE-pre. CVG had a significant Assessment effect, $F(2,16) = 3.84$, $p = 0.044$), with complexity values for IE-post significantly higher than for IE-pre ($p = 0.042$), but no different from VG ($p = 0.484$) according to Bonferroni-corrected post hoc comparisons. The Assessment × Scale interaction was significant as well, $F(3.800, 30.401) = 3.04$, $p = 0.034$, with significant differences for the second to fourth scales ($p < 0.047$). These results are illustrated in Figure 23. Descriptive statistics are available in Table 15.

Summary of Results

Motor performance. As expected, there were no differences in measures of relative phase, period, and amplitude among groups in IE-pre. All groups except CTRL improved from IE-pre to IE-post. The only group that was significantly better than CTRL, however, was NVG. Only CTRL obtained an accuracy benefit from VG, as the additional improvement seen for the other groups was not significant compared to IE-post.

With respect to RMSE of the target relative phase, it was again the case that all groups except CTRL demonstrated improvement in IE from pre to post. Again, NVG was the only group with significantly lower RMSE relative to CTRL. In the VG assessment no additional benefits were conferred on CVG or FVG compared to IE-post, and in fact worse performance was observed for NVG. Performance in the VG assessment was significantly better for CVG and FVG compared to NVG and CTRL.

Stability of relative phase improved significantly for CVG and NVG, but groups were not significantly different from each other in IE-post. In VG, only CVG showed significantly improved performance compared to IE-pre. Compared to IE-post, a decrement in stability was observed for NVG in VG. Stability of CVG and FVG in the VG assessment was significantly better compared to CTRL.

Perceptual performance. HPRP did not reveal any group differences. Averaged across all angles and groups, the absolute error, root mean square error and standard deviation of haptic perceptual judgments were slightly lower in the second assessment but the differences were only marginally significant. Root mean square error values for the judgments at 90° were significantly lower after practice.

Temporal correlations. Temporal correlations also did not show group effects, or any change between IE-pre and IE-post. Averaged over groups, temporal correlations in the series of phases was significantly lower for VG. Temporal correlations for the series of amplitudes were also lower for VG, with a decrease of greater magnitude observed for CVG. The temporal correlations over periods did not change between the three assessments.

Complexity. Complexity of phases did not differ between assessments or between groups. For amplitudes, CTRL did not show changes in complexity from IE-pre to IE-post, the increase observed for NVG and FVG was not statistically significant, and CVG showed a significant increase in complexity. While CTRL demonstrated a decrease in complexity in the VG assessment, CVG maintained similar complexity levels. The decrease observed in NVG and FVG did not reach statistical significance.

For complexity of periods, CTRL once again did not show changes in complexity from IE-pre to IE-post and showed a significant decrease in VG. For NVG, complexity exhibited in VG was also lower than that for IE-post, and not significantly different from IE-pre. FVG showed the same effect but only for the first four scales. CVG, in contrast, increased significantly in complexity from IE-pre to IE-post, and did not show a significant decrease in VG.

Discussion

This experiment was conducted to investigate the effects of practice under different perceptual constraints on the learning of a bimanual coordination pattern. It was expected that the loss of complexity and the weakening of temporal correlations in synergy organization under visual guidance would impact synergy organization for IE. More specifically, it was expected that for individuals who practiced under constant visual guidance, refinement of haptic perception of relative phase, movement stability, temporal correlations and complexity of movement dynamics would be lower than for individuals who practiced under no visual guidance.

No changes in HPRP were observed. Given the importance of haptic perception of relative phase for stable performance of bimanual coordination patterns, the lack of differential effects of visually guided practice on HPRP could be taken as evidence against the hypothesis that VG obviates the refinement of haptic perception. Limitations of the methods used in the present study, however, could account for the negative findings. First, there is some possibility of ceiling effects on the initial assessment. Second, the apparatus did not allow testing for the perception of variability of relative phase. Not only the ability to perceptually resolve relative phase but also to resolve phase variability play an important role in the stability of movement patterns (Bingham, 2004). Haptic perception in a bimanual task allows for more accurate judgments of pattern stability than do visual displays of simulated bimanual motion (Wilson et al., 2003), in line with the factorization of attractor strength and attractor location to the levels of synergies (focused on muscular-proprioceptive information) and space (focused on visuo-spatial constraints). If attractor strength is indeed intimately connected to haptic perception of phase variability, differences between groups could have been missed by lack of specific testing.

Continuing the factorization issue, guidance by vision appears to favor attractor location (accuracy) at the expense of strength (stability), at least in the initial phases of practice (see also Kovacs et al., 2010). Descriptive statistics on the evolution of performance over practice trials (see Figures 10 to 12) showed that mean phase was immediately closer to the target for CVG and FVG compared to NVG, while stability (SD) was lower for CVG and FVG, and better for NVG. Naturally, in the initial stages of learning, visual guidance by information about relative phase as provided by Lissajous plots allows for detection and subsequently correction of errors in achieving the goal pattern. This error correction process may then lead to increased variability, as the individual transitions between the initial pattern and the goal pattern. Even after the end of practice, however, for NVG, the group with best performance, Lissajous guidance in the VG test improved accuracy but reduced stability (see also Kovacs & Shea, 2011). Practice without vision, in turn, favors stabilization of coordination at the expense of accuracy. Individuals settle in on a stable coordination pattern, but there is a risk, however, that this pattern may not be the required pattern (Kovacs et al., 2010). In Experiment 2, the provision of visual performance feedback after each trial block may have been essential for the improvement in accuracy demonstrated by NVG.

Contrary to expectation, in IE-post the stability of relative phase was not significantly different between groups. Although the improvement in stability of greatest magnitude was seen for NVG, with SD reaching a mean value around 26° for this group and 35° to 40° for the other groups, intra-group variability was high and between-group differences were not statistically significant. The composite of stability and accuracy, root mean square error, however, though improved for all practice groups, was indeed better after practice only for NVG compared to CTRL. Likewise, accuracy of performance alone (mean phase) was best in NVG. In general, because CVG and FVG failed to perform significantly better than CTRL in IE-post despite their improvement, results offer support for the prediction that practice with guidance decreases the possibility of acquiring and retaining the ability to perform the goal pattern independently (with no guidance). Note that FVG could have been expected to present the best performance results, as previously demonstrated by Kovacs and Shea (2011). A fading schedule of guidance would have created the opportunity to take advantage of both visual information for accuracy and haptic differentiation for stabilization of coordination, thus avoiding detrimental guidance effects. In the aforementioned study, however, the improvement of participants in the fading guidance group might have been inflated, comparatively to those that received no guidance, given that this last group received no performance feedback whatsoever. In the present study, visual feedback of performance after each block of 8 trials was apparently sufficient to supersede the learning benefits of a fading schedule of guidance.

It was speculated that changes in the dynamical organization of synergies under different perceptual constraints would underlie the effect of practice conditions on the acquisition of independent performance of a new coordination pattern. Results did not offer support for this speculation, but there is reason to believe that they have implications for the interpretation of $1/f$ variability and complexity in movement coordination.

Changes in temporal correlations of phases, periods and amplitudes did not parallel changes in motor performance in IE-post. Contrary to expectations based on previous findings, there was no strengthening of temporal correlations in the direction of $1/f$ (Wijnants et al., 2009). While $1/f$ variation, in the strict sense, is characterized by $\beta = 1$ and $\alpha = 1$, for characterization of experimental series the definition is usually extended so that 1/*f* variation encompasses the range $0.5 < \beta < 1.5$ or correspondingly, $0.75 < \alpha < 1.25$ (Wagenmakers, Farrell, & Ratcliff, 2004). In IE-pre, temporal correlations of phases and amplitudes had already demonstrated 1/*f* structure with α around 0.79 and 0.84, respectively, while for periods α was around 0.73. The values of α remained at similar levels in IE-post. The lack of significant changes could be due to limitations of the estimation methods. It is known that the variability of scaling exponents obtained with DFA tends to increase for short series with $\alpha > 0.5$ (Delignieres et al., 2006), as was the case in Experiment 2. This increased variability of estimates decreases the likelihood of finding statistically significant differences when comparing group means.

Assuming, however, that the lack of significant differences is not a result of inflated estimation variability, these results have implications for the interpretation of 1/*f* variation in human performance. In VG, consistently with Experiment 1, α for phases and amplitudes was significantly lower. For amplitudes, CVG had the greatest reduction in α, probably as a reflection of optimized entrainment to the visual information due to practice. It thus appears that the structure of temporal correlations may capture differences in the ability to entrain to and incorporate guiding information into movement organization but not the ability to produce stable and accurate patterns of movement coordination. It appears that *1/f structure may be a marker of independent, self-controlled performance but not necessarily of skillful as opposed to inexperienced performance.* Given the paucity of studies investigating the association of learning-related performance improvement and changes in temporal correlations, and the conflict between present results and previous findings, the issue needs further investigation. Complexity measures, in turn, did reveal some changes with learning. Also in this experiment, these findings indicate that complexity measures seem to capture aspects of dynamics not captured by DFA.

No changes in complexity of relative phase series were found. Complexity of amplitudes and periods did reveal changes after practice. In general, means of the three experimental groups increased for IE-post. Several differences failed to reach significance, however. Surprisingly, the most consistent changes were seen for CVG. This could be related to reduced intra-group variability due to tighter performance constraints provided by visual guidance during practice. For both amplitudes and periods, a significant increase in complexity of IE-post was observed. For VG, while there was in general a decrease in complexity, CVG was able to perform with similar complexity in the within and cross-series (right and left hands) dependencies of amplitudes and periods. Note that because analysis involved multivariate series composed by right and left hand data, complexity values for periods and amplitudes do not solely refer to components of the bimanual pattern but capture aspects of their coordination.

It was speculated that higher complexity levels indicate active degrees of freedom varying with greater concinnity and interdependence. If so, learning would proceed with increases in complexity. Support for this prediction was not strong, as it was confirmed not for phases but only for amplitudes and periods, and did not reach significance for all practice groups. Additionally, it was expected that lower complexity in practice conditions would negatively impact the organization of synergy for independent execution, underlying the effects predicted by the guidance hypothesis. Confirmation of this prediction would have required that CVG demonstrated lower complexity by the end of practice compared to the other groups, and that was not the case.

It is interesting to note that similarly to Experiment 1, temporal correlation and complexity measures seem to be capturing distinct aspects of dynamics. Here a whitening of temporal correlations for the series of amplitudes of CVG in the VG assessment was accompanied by conservation of complexity in the composite series of right and left hand amplitudes. Apparently, the more intense whitening for CVG resulted from a greater possibility to rely on guidance—an effect of specificity to practice conditions for participants of CVG. Conservation of complexity for this group may be viewed in light of simulation studies. DFA results indicate whiter variation for right hand data, which should be accompanied by lower complexity results. According to simulations, bivariate uncorrelated series of white noise are less complex than bivariate uncorrelated series of 1/*f* noise. For correlated bivariate series of white noise however, MEMD-enhanced Multivariate MSE indicates, over several temporal scales, higher entropy values than for uncorrelated bivariate 1/*f* series (Looney, Ahmed, & Mandic, 2012). Therefore, the origins of complexity maintenance for right and left hand bivariate series in spite of whitening of right hand data lie in the pattern of component relationships that take place in coordination. This maintenance of complexity is consistent with the reasoning that, if the explanation of complexity is to be found in universal (Van Orden et al., 2003) rather than special principles (given that complexity is seen across diverse natural systems with little in common), even if experimental manipulations alter the expression of complexity in measures chosen for analysis, it is unlikely that, as a result of these experimental manipulations, human coordination has ceased to be complex or multileveled (Torre & Wagenmakkers, 2009). The intrinsic complexity of the system is still at work after practice under visual guidance but is expressed differently in overt performance (Delignieres & Torre, 2009).

Why, on that account, would these complex component coordination patterns not have been seen in the chosen measures made on the other groups in Experiment 2, those that showed a decrease in complexity in VG? The answer possibly relates to the support, albeit modest, for the speculation that complexity increases with learning. CVG practiced and learned to coordinate optimally with visual guidance to produce the target pattern, while the other groups did not. *Complexity appears to reflect not some general characteristic imposed by tasks but a unique assembly of perception-action processes for an individual performing a particular task* (Torre, Balasubramaniam, Rheaume, Lemoine, & Zelaznik, 2011). Said differently, lower complexity is not characteristic of performance under visual guidance in general. Instead, complexity under guidance by a Lissajous plot, for the measures chosen in Experiment 2, depends on individual experience.

Experiment 2 was conducted under the general motivation of investigating how perceptual manipulations could help overcome coordination constraints and affect learning. Visual guidance by means of simplified information integrating component motions into one simple perceptual goal pattern has been shown to affect the coupling between the two limbs, facilitating effective production of a wide range of bimanual coordination patterns (Kovacs et al., 2009a, b; Kovacs & Shea, 2010, 2011; Kovacs et al., 2010). These effects on performance have not been translated to learning, given the evidence of performance deterioration with guidance withdrawal (Kovacs & Shea, 2011). We expected that differences in the refinement of perceptual ability and in the dynamics of movement coordination with and without guidance would underlie this guidance effect. Results did not support our expectations, but pointed to an interpretation of $1/f$ structure that relates more to self controlled than to proficient performance, and to an interpretation of complexity that relates more to individual-specific and task-specific use of resources than to a general nature of tasks or performance level.

Appendix A: Report on an additional planned experiment

Experiment 1 investigated the effects of visual guidance specific to phase and amplitude on synergy architecture and the structure of movement variability. It is the thoroughness of haptic perception, however, that guarantees the fluidity and context sensitivity of coordinated movement patterns expressed at the level of synergies (Bernstein, 1996). Given the crucial role of haptic information for self-controlled, independent execution of coordination patterns, the initial ability in a coordination pattern not readily available such as 90° should be related to haptic perceptual ability. Additionally, if the dynamics of synergies enfold perception and action (Turvey, 2004), it is necessary to verify if dynamical measures such as complexity and the structure of variability over time bear any explicit relation to perceptual and motor ability. The investigation of the relationships between the dynamics of movement organization, haptic perceptual ability and motor performance would help increase the understanding of what factors favor self-monitored, independent performance, which is the eventual goal when learning a new coordination pattern. The second experiment planned for this thesis would investigate these relations.

More specifically, for 55 participants (data from 44 of them coming from the experiment reported in chapter 3) data was collected following procedures described for the first assessment session in chapter 3. Dynamics of movement organization was characterized with measures of temporal correlation (DFA) and complexity (MEMD-enhanced Multivariate MSE). Motor performance was characterized with measures of accuracy (mean phase), stability (standard deviation of phase) and a composite measure of accuracy and stability (root mean square error of phase), as well as descriptive measures (means and standard deviations) for amplitudes and periods. Perceptual ability was characterized with scores from the perceptual task reported in chapter 3.

We expected to find correlations between stability of haptic perceptual judgments at 90° of relative phase and stability of movement coordination at the same relative phase, (Bingham, 2004; Wilson et al., 2003), as well as between temporal correlations and perceptual performance (Palatinus, Dixon, & Kelty-Stephen, 2013; Stephen, Arzamarski, & Michaels, 2010; Stephen & Hajnal, 2011). The structure of variability over time was also expected to correlate with motor performance, which would encompass the online use of information to allow one to produce the goal pattern stably and accurately. Some studies have reported a correlation between complexity and motor performance (Newell & Vaillancourt, 2001; Newell, Vaillancourt & Sosnoff, 2006; Vaillancourt & Newell, 2002) These studies, however, have used single scale entropy measures that in fact only speak to regularity, not complexity (see Appendix B for an overview of complexity measures). Thus no specific hypothesis were formulated regarding the association of multiscale complexity measures and other variables.

No consistent pattern of correlations was found between analyzed variables. No perceptual variables were significant predictors of accuracy or stability of relative phase. The strength of temporal correlations of phases did not correlate with any motor or perceptual variables. The standard deviation of phases, amplitudes and periods were predicted by complexity indices, calculated by summation of entropy values across temporal scales (see Appendix B and Data reduction section of chapter 3 for definitions). In general, standard deviations were negatively related to indices defined over finer/faster scales and positively related to indices defined over coarser/slower scales. Because most findings were negative and he meaning of these few significant relations was not clear, we decided not to report this experiment in the main text.

Appendix B:

Limitations encountered in applying phase space reconstruction to quantify dimensionality

Phase space reconstruction (Abarbanel, 1996) has been used to quantify the dimensionality of synergies. More specifically it has been used to quantify the number of active (dynamical) degrees of freedom (ADF), which refers to the minimal number of first order autonomous differential equations needed to capture the time evolving dynamics of a system. The concept captures the dynamical variables brought into play during execution of a coordination pattern (for a tutorial see Mitra et al., 1998). Vision has been shown to produce effects on ADF for an intra-limb synergy, inducing a reduction in the number of ADF when a unimanual oscillatory precision task is guided by vision (Mitra et al., 1998). The effect of vision on the number of ADF of bimanual coordination tasks has not been investigated to date. We intended to investigate the possible influence of vision on this aspect of graph dynamics by quantifying the number of ADF. Below we describe the method, report the results obtained for data of Experiment 1 and discuss possible reasons for the inconsistent results.

Method

The method is based on the fact that dissipative systems evolve asymptotically toward low-dimensional attractors that define their dynamical properties. Phase space reconstruction is rooted in mathematical topology and based in a time-delay embedding procedure of attractor reconstruction (Abarbanel, 1996; also see Mitra et al., 1998 for a tutorial). A given time series is embedded in higher-dimensional spaces constructed from a time-series and time-lagged copies of it. Fundamental topological invariants of the original unknown dynamics are preserved in the reconstructed phase-space. According to the embedding theorem (Takens, 1981), this can be done based on essentially any measured variable, because all of the system variables are assumed to be coupled (being precisely this coupling that puts the system into attractors).

Therefore we assume that the one-dimensional measured scalar time series x(t) of hand position data is a lower dimensional projection of the full dynamics of the attractor characterizing the synergy. By phase space reconstruction, x(t) was embedded in a space of vectors y(t) whose coordinates are [x(t), x(t + Tτ),x(t + 2Tτ),…], where T is some integer multiple of the sampling period , and τ is an appropriate time delay defined by the first minimum the Average Mutual Information function, a probabilistic measure of the extent to which x(t + τ) is related to x(τ) at a given τ. Use of the first minimum introduces statistical independence between successive lagged values, so that addition of a series at that lag is most effective in revealing new information about the original dynamics.

Once the series is embedded in this reconstructed phase space, a determination of the number of ADF, the number of dynamical variables needed to describe the local evolution of the system around its attractor can be made. The number of ADF is thus a measure of local dimensionality of a subspace of the embedding space where the solution manifold of the systems equations live. The number of ADF is an invariant o the dynamics, so that it does not depend on the choice of measurement variable.

The local false nearest neighbors method (Abarbanel, 1996) was used to estimate the number of ADF. The method is based on the idea that as soon as dimensionality of the attractor is sufficient, predictions of evolution of the dynamics along the attractor will be accurate. Characterization of the attractor with insufficient dimensions, however, will lead to inaccurate prediction due to artifacts of projection of the dynamics in a space of lower than needed dimensionality. The method proceeds by specifying the number of neighbors at a point in the attractor and abstracting a local prediction rule (polynomial regression) for how those neighboring points evolve in time. First, different sized neighborhoods of data points (here 40, 60, 80 and 100 neighbors) are taken in subspaces of different dimensions (here up to 12). The prediction of their local evolution on the attractor is then checked for errors greater than a set fraction (here equal to 0.3) of the attractor size (Abarbanel, 1996; Goodman, Riley, Mitra, & Turvey, 2000; Mitra, Riley, & Turvey, 1997). The number of ADFs is the dimension number at which the percentage of bad predictions fails to improve with added subspace dimensions and becomes independent of neighborhood size.

Because we were not interested in handedness effects, only the series of right hand one-dimensional displacements were used for phase space reconstruction. Because the analysis requires stationary signals, empirical mode decomposition (EMD) was used to detrend all time series before phase space reconstruction. While Fourier methods linearly decompose the signal as combination of sines and cosines and are insufficient for dealing with nonlinear and nonstationary signals (Akay, 1999), EMD is a data driven method specifically developed for decomposing nonlinear, non-stationary signals into their intrinsic frequency components (Huang et al., 1998; Rilling et al., 2003). The successive components obtained with EMD are called intrinsic mode functions. Different intrinsic mode functions capture the properties of the original signal on different time scales. The first extracted intrinsic mode function is the highest frequency component in a signal containing plenty of detail. The subsequent intrinsic mode functions are narrowband and monocomponent, with the characteristic frequency decreasing with the intrinsic mode function number. The last intrinsic mode function is the overall trend (see Figure 24 for an illustration). Even if the original signal is non-stationary, the intrinsic mode functions are much better conditioned and are typically quasi-stationary (Ahmed et al., 2012). The right hand movement series were detrended by subtracting the intrinsic mode functions of lowest frequency from the original time series (Costa et al., 2007). Only those intrinsic mode functions containing frequencies lower than one tenth of the main signal frequency were removed, in an effort to make the series appropriately stationary for phase space reconstruction while minimizing the loss of relevant structure with the detrending process. The Contemporary Signal Processor software (chaotic.com, Great Falls, VA) used for phase space reconstruction processing.

Results

To determine the number of ADF via phase space reconstruction, the % of bad predictions per neighborhood size per added local dimension were calculated for each participant and averaged over the two trials per condition. A 2 (Group) × 3 (Condition) × 12 (Dimension) × 4 (Neighborhood size) mixed ANOVA showed no significant effect for Group, $F < 1$, or any of the interaction effects with Group ($p > 0.13$). Group therefore was not included as a factor in subsequent analyses.

A 3 (Condition) × 12 (Dimension) × 4 (Neighborhood size) repeated measures ANOVA showed a significant interaction between Condition and Dimension, $F(22, 660) = 9.09$, $p < 0.001$) and Condition and Neighborhood size, $F(6, 180) = 2.76$, $p = 0.027$. To further examine the differences originating these effects, in subsequent steps, 12 (Local Dimension) × 4 (Neighborhood Size) repeated measures ANOVAs were used to look into each Condition separately. When a significant interaction between these two factors was found for a given Condition, subsequent repeated measures ANOVAs including progressive fewer dimensions were used to investigate the origins of the interaction and detect where the % of bad predictions failed to vary with dimension and with neighborhood size. The dimension at which this happened was taken as the number of ADF for a quantification of dimensionality. Results reported below are illustrated in Figure 25.

Visual Guidance

A 12 (Dimensions) × 4 (Neighborhood sizes) ANOVA showed a significant interaction effect, $F(33, 990) = 5.47$, $p < 0.001$. ANOVAs including Neighborhoods (4) and Dimensions (2 to 12, thus 11 dimensions, 3 to 12, thus 10, dimensions, 4 to 12, thus 9 dimensions and so on) indicated that main effects and interaction effects stopped being significant when dimensions 8 to 12 and the 4 neighborhood sizes were considered ($p > 0.10$ after the H-F correction). The results of these ANOVAs including progressive fewer dimension levels indicated that from subspace dimensions 8 to 12, the percentage of bad predictions failed to improve with added subspace dimensions and became independent of neighborhood size. The number of ADF for VG was therefore 8.

Metronome Pacing

A 12(Dimensions) × 4(Neighborhood sizes) ANOVA showed a significant interaction effect, $F(33, 990) = 9.375$, $p < 0.001$. ANOVAs including progressive fewer dimension levels and the 4 Neighborhoods levels indicated that main effects and interaction effects stopped being significant when dimensions 9 to 12 and the 4 neighborhood sizes were considered ($p > 0.49$ after the H-F correction). The results of these ANOVAs including progressive fewer dimension levels indicated that from subspace dimensions 9 to 12, the percentage of bad predictions failed to improve with added subspace dimensions and became independent of neighborhood size. The number of ADF for MP was therefore 9.

Independent Execution

A 12 (Dimensions) × 4 (Neighborhood sizes) ANOVA showed a significant interaction effect, $F(33, 990) = 9.19$, $p < 0.001$. ANOVAs including progressive fewer dimension levels and the 4 Neighborhoods levels indicated that main effects and interaction effects stopped being significant when dimensions 7 to 12 and the 4 neighborhood sizes were considered ($p > 0.395$ after the H-F correction). The results of these ANOVAs including progressive fewer dimension levels indicated that from subspace dimensions 7 to 12, the percentage of bad predictions failed to improve with added subspace dimensions and became independent of neighborhood size. The number of ADF for IE was therefore 7.

Comparison of % bad predictions between conditions

Considering that the higher subspace dimension at which the % of bad predictions stabilized was 9 (for CM), a 3 (Conditions) × 4 (Dimensions 9 to 12) × 4 (Neighborhood sizes) ANOVA was used to compare the % of bad predictions between conditions. Only a significant effect of Conditions was found, $F(2, 60) = 48.84$, $p < 0.001$). Contrasts showed that VG had a significantly higher % of bad predictions than MP ($p < 0.001$) and IE ($p < 0.001$), while the values for MP and IE did not differ significantly ($p = 0.127$).

Considerations on results and methods

The number of ADF as determined by phase space reconstruction was ordered from IE to VG to MP. These conditions had 7, 8 and 9 ADF respectively. The final % of bad predictions (at the dimensions at which it was no longer varying for any of the conditions) was significantly higher for VG. Groups did not influence results.

Measures of ADF and complexity indicated changes in graph dynamics, suggesting a qualitative reorganization of the underlying movement synergy to perform the anti-phase pattern. The simplification of the task with the use of visual guidance therefore apparently does not just facilitate task execution regardless of the complexity of movement details. Instead, results suggest it can change the complexity of movement organization itself. This interpretation is supported by multivariate multiscale complexity analysis as well as by phase space reconstruction results. Phase space reconstruction results should be critically evaluated with respect to previous findings and viewed with caution.

Our results did not replicate previous findings with respect to the approximate number of ADF characterizing unimanual and bimanual coordination using the same conventional recommendations for neighborhood size and the threshold for determining false nearest neighbors (Abarbanel, 1996). Goodman et al. (2000) used phase space reconstruction for unilateral oscillations of a hand-held pendulum at resonant and non-resonant frequencies and found 3 and 4 ADFs, respectively. Mitra et al. (1997) similarly found 3 and 4 ADF for the same task performed with pendulums of different values of rotational inertia. For unimanual series of individuals learning to coordinate their wrist movements at 90°, Mitra et al. (1998) found 4 to 5 ADFs. Moreover, the number of ADF for unimanual oscillations dropped from 4 to 3 when participants performed a rhythmic aiming task with the limb fully visible (Mitra et al., 1998). Results of the present study indicated, however, 7, 8 and 9 ADFs for IE, VG and MP respectively, for the dynamics of right hand movement during bimanual anti-phase coordination.

The failure to replicate previous findings might be related to three factors. First, data of Experiment 1 might have been affected by noise, either due to measurement or intrinsic to the dynamics. Noise can be amplified by embedding procedures (Casdagli, Eubank, Farmer, & Gibson, 1991). Second, EMD as applied to the data might have failed to completely remove nonstationarities. There is no agreement on a definition of stationarity and no definitive formal test to confirm or exclude its presence (Schreiber, 1999). Third, temporal correlations might be present in the data. Processes with power law correlations over temporal scales are often considered nonstationary since no length of measurement could ever cover all time scales. This leads to a dependence of dimensionality results on the length of the time-series.[8] To test this possibility in the present study, the analysis was repeated for the first 30 seconds of each series (to obtain series with lengths closer to those used in the previous coordination studies cited above) and used the same statistical criteria to define the number of ADF. The number of ADF remained at 7 for IE, but dropped to 6 for VG and to 7 for MP. DFA and $^{low}PSD_{we}$ indicated the presence of temporal correlations in the series of amplitudes, periods and phases but due to the periodicity of hand displacements, DFA and $^{low}PSD_{we}$ are not suited to analyze these series. Further analysis suited to characterize temporal correlations in periodic data (see for example Horvatic, Stanley, & Podobnik, 2011; Anastas, Stephen, & Dixon, 2011; Kelty-Stephen, Palatinus, Saltzman, & Dixon; 2013) could be attempted in the future.

[8] This dependence has been demonstrated for the correlation dimension and for false nearest neighbors methods of testing for nonlinearity (Kennel & Abarbanel, 2002; Osborne & Provenzale, 1989). We assume it may also affect the present measure of ADF, which is based on local false nearest neighbors statistics and is theoretically closely related to the correlation dimension as an alternative invariant measure of dimensionality.

Appendix C: Rationalizing the choice for complexity measures

Multivariate Multiscale Entropy (Multivariate MSE) after Multivariate Empirical Mode Decomposition (MEMD) (Ahmed & Mandic, 2011, 2012; Ahmed et al., 2011; Ahmed et al., 2012) was used to quantify complexity in this study. MEMD-enhanced Multivariate MSE was proposed to overcome limitations identified in traditional entropy estimation methods. The Kolmogorov-Sinai (KS) entropy (Grassberger & Procaccia, 1983), for instance, which is based on the Shannon entropy (Shannon, 1948) and applicable to stationary processes, measures the mean rate of decrease of uncertainty at a receiver by knowing the current state of the system given the past history. This measure is known to produce severe underestimation for real world finite length series (Costa et al., 2005). Modifications proposed to achieve better precision (Eckmann & Ruelle, 1985; Grassberger & Procaccia, 1983) have been shown to be not useful for data contaminated with any amount of noise and thus not applicable to biological experimental series (Costa et al., 2005). For the analysis of short and noisy time series, Pincus (1991) introduced a family of measures termed Approximate Entropy (ApEn), intended to function as a regularity statistic for 'real world' time series, rather then to approximate previous methods. The Sample Entropy (SampEn) of a time series is a refinement of ApEn, a measure of an ‘‘orderly structure’’ in a time series that tests if there are any repeated patterns of various lengths, including those that may not be repeated at regular intervals. SampEn measures the negative logarithm of the conditional probability that two sequences that are similar for m points, remain similar at the next point, within a tolerance r. Compared to ApEn, SampEn is less dependent on time series length, and shows relative consistency over a broader range of possible r and m values (Richman & Moorman, 2000).

Both ApEn and SampEn are maximized for completely random processes and quantify the regularity or predictability of time series on the single scale determined by data collection methods. In reality however, time series derived from complex systems have multiple spatiotemporal scales, and single-scale entropy based measures may lead to misleading results, yielding, for example, higher values for surrogate series obtained by random shuffling procedures that destroy the correlational structure in comparison to the original series. These measures therefore cannot reflect complexity. Multiscale Entropy (MSE) was proposed to better capture the presence of structural complexity in a time series by calculating SampEn over different temporal scales defined by a coarse graining procedure. With this procedure, sequential time scales are constructed by taking averages of data points within adjacent windows of increasing length. Results of MSE are consistent with the intuitions that neither highly ordered (e.g. periodic) nor maximally disordered (random) systems possess complex structure (Zang, 1991). SampEn values obtained across scales with MSE reveal higher complexity for temporally correlated series (Costa et al., 2002, 2005). Figure 26 illustrates this finding with a multivariate version of MSE, as explained below.

Shortcomings of MSE include elimination of high-frequency components due to the coarse graining procedure, which is especially problematic when the relevant information is contained in these components, as may be the case for some biological data. The coarse graining process also reduces the input data length to half its original size for each successive scale, potentially decreasing the reliability of the estimates. Additionally, the temporal scales defined by MSE do not necessarily match the intrinsic dynamical scales of the series. More importantly, the method is inadequate for nonstationary and nonlinear signals. If a signal contains one or more pronounced trends, they can severely bias sample entropy calculations (Ahmed et al., 2012).

The proposed strategy to overcome these issues is to calculate entropy over multiple oscillatory levels defined by intrinsic mode functions extracted with Empirical Mode Decomposition (EMD) (Amoud et al., 2007; Hu & Liang, 2012), or the multivariate version of EMD (MEMD), for multivariate time series. EMD is a data driven method specifically developed for decomposing nonlinear, non-stationary signals into their intrinsic frequency components (Huang et al., 1998; Rilling et al., 2003). The successive components obtained with EMD are called intrinsic mode functions. Different intrinsic mode functions capture the properties of the original signal on different time scales. The first extracted intrinsic mode function is the highest frequency component in a signal containing plenty of detail. The subsequent intrinsic mode functions are narrowband and monocomponent, with the characteristic frequency decreasing with the intrinsic mode function number. The last intrinsic mode function is the overall trend (see Figure 24 for an illustration). Even if the original signal is non-stationary, the intrinsic mode functions are much better conditioned and are typically quasi-stationary (Ahmed et al., 2012). MEMD, the multivariate version of EMD, can simultaneous decompose two (Rilling et al., 2007), three or more time series (Rehman & Mandic, 2010) with the advantage of mode alignment property, meaning that the intrinsic mode functions generated for each series of the multivariate series set are same in number and belong to the same frequency band, making their comparison meaningful (Ahmed et al., 2012).

The intrinsic mode functions can be used to generate multiple intrinsic data scales. These scales can be ordered from fine-to-coarse or coarse-to-fine by the cumulative sums of sequential intrinsic mode functions. To generate fine-to-coarse scales, the sums of all intrinsic mode functions from first to last, second to last, third to last and so on are taken. The first scale thereby defined contains the original signal, while the last contains the slower varying trend. To define coarse-to-fine scales, the sum of all intrinsic mode functions, all but the last one, all but the last two, all but the last three and so on are taken. This way the first scale also contains the full original signal and the last contains the intrinsic mode function of higher frequency content (Hu & Liang, 2012). Because intrinsic mode functions are narrow-band quasi-stationary signals, SampEn (and also its multivariate version, see below) can then calculated for the scales defined with intrinsic mode functions. Additionally, high frequency content is not lost and each scale contains the same number of data points as the original signal. Only measures regarding coarse-to-fine scales are reported in this dissertation.

Once the scales are constructed, SampEn or its multivariate version MSampen (Ahmed & Mandic, 2011; Ahmed et al., 2012) are calculated across the scales. MSampEn is based on multivariate embedded reconstruction with composite delay vectors, with a typical time lag t =1. It enables entropy calculation for multivariate time series data, taking into account both within and cross-series dependencies. Standardization (transformation to z-scores) of the series is generally used prior to SampEn or MSampEn calculation to allow for a similar threshold criterion across all time series. Both the multivariate MSE and the MEMD-enhanced Multivariate MSE reveal higher complexity for temporally correlated series (pink noise) compared to uncorrelated series (white noise) as illustrated in Figure 26 (Ahmed et al., 2012).

All Matlab codes used in this study for complexity measures were made publicly available online by their authors. Bivariate EMD can be found at

http://perso.ens-lyon.fr/patrick.flandrin/emd.html,

MEMD can be found at

http://www.commsp.ee.ic.ac.uk/~mandic/research/emd.htm,

and MSampen can be found at

http://www.commsp.ee.ic.ac.uk/~mandic/research/Complexity_Stuff.htm.

SampEn is available at http://www.physionet.org/physiotools/sampen/.

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Table 1. *Descriptive Statistics in Experiment 1.*

Performance measure	Group	Condition	*Mean*	*SD*
Accuracy	A	IE	178.70	4.42
		MP	178.10	5.90
		VG	176.95	7.92
	B	IE	175.60	5.99
		MP	176.98	8.27
		VG	179.66	4.80
Stability	A	IE	19.50	7.60
		MP	20.51	6.39
		VG	37.08	17.53
	B	IE	18.72	3.70
		MP	19.61	4.11
		VG	31.45	10.02
Pace	A	IE	0.39	0.07
		MP	0.38	0.07
		VG	0.43	0.18
	B	IE	0.43	0.08
		MP	0.42	0.07
		VG	0.76	0.40

Table 2. *Descriptive Statistics for Temporal Correlation Measures for the Series of Relative Phases in Experiment 1*

Group	Condition	DFA α		$^{low}PSD_{we}$ β	
		Mean	*SD*	*Mean*	*SD*
	IE	0.66	0.07	0.31	0.16
A	MP	0.67	0.04	0.34	0.11
	VG	0.57	0.08	0.10	0.27
	IE	0.65	0.07	0.37	0.20
B	MP	0.70	0.09	0.38	0.22
	VG	0.53	0.06	0.12	0.18

Table 3. *Descriptive Statistics for Temporal Correlation Measures for the Series of Amplitudes in Experiment 1*

Group	Condition	DFA α		$^{low}PSD_{we}$ β	
		Mean	*SD*	*Mean*	*SD*
A	IE	0.96	0.06	1.04	0.12
	MP	0.96	0.07	0.99	0.19
	VG	0.86	0.11	0.73	0.24
B	IE	0.95	0.07	0.93	0.22
	MP	0.98	0.07	0.96	0.18
	VG	0.73	0.11	0.55	0.24

Table 4. *Descriptive Statistics for Temporal Correlation Measures for the Series of Periods in Experiment 1.*

Group	Condition	DFA α		$^{low}PSD_{we}$ β	
		Mean	*SD*	*Mean*	*SD*
A	IE	0.68	0.10	0.60	0.19
	MP	0.41	0.23	0.05	0.58
	VG	0.67	0.11	0.43	0.25
B	IE	0.69	0.09	0.65	0.26
	MP	0.41	0.25	0.04	0.58
	VG	0.71	0.07	0.53	0.30

Table 5. *Descriptive Statistics for Average Complexity of Relative Phase (Mean Across Scales) Per Condition and Group in Experiment 1.*

Group	Condition	Average Complexity	
		Mean	*SD*
A	IE	1.59	0.56
	MP	1.63	0.60
	VG	0.73	0.31
B	IE	1.82	0.38
	MP	1.95	0.32
	VG	0.91	0.41

Table 6. Descriptive Statistics for Average Complexity of Bivariate Amplitude Series (Mean Across Scales) Per Condition and Group in Experiment 1.

Group	Condition	Average Complexity	
		Mean	*SD*
A	IE	1.60	0.10
	MP	1.61	0.10
	VG	1.34	0.20
B	IE	1.62	0.08
	MP	1.62	0.07
	VG	1.45	0.13

Table 7. *Descriptive Statistics for Average Complexity of Bivariate Period Series (Mean Across Scales) Per Condition and Group in Experiment 1.*

Group	Condition	Average Complexity	
		Mean	*SD*
A	IE	1.61	0.07
	MP	1.64	0.09
	VG	1.20	0.38
B	IE	1.60	0.08
	MP	1.64	0.08
	VG	1.39	0.18

Table 8. *Descriptive Statistics for Performance Measures in Experiment 2*.

Group	Assessment	Accuracy		Stability		Composite accuracy and stability	
		Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
CTRL	IE-pre	136.95	27.36	48.11	11.67	70.11	18.18
	IE-post	133.54	30.97	40.26	10.33	62.74	22.97
	VG	89.27	5.37	49.67	17.09	52.09	15.69
NVG	IE-pre	128.93	33.94	50.96	24.50	66.76	26.94
	IE-post	94.87	7.88	26.51	7.77	29.25	8.53
	VG	90.63	11.38	40.85	19.04	44.34	18.76
FVG	IE-pre	152.39	29.55	42.32	16.98	76.26	24.72
	IE-post	100.28	32.70	37.17	25.91	45.27	26.82
	VG	89.82	1.69	24.67	3.34	25.45	3.56
CVG	IE-pre	132.82	32.08	46.09	15.91	69.92	19.75
	IE-post	117.74	34.10	35.83	18.04	51.18	29.47
	VG	89.83	3.84	24.08	6.03	24.92	6.80

Table 9. Descriptive statistics for HPRP in Experiment 2

		Angle																	
		0°		22.5°		45°		67.5°		90°		112.5°		135°		167.5°		180°	
Group	Measure	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
CG	AE pre	9.95	10.15	18.35	7.97	31.28	8.57	30.48	10.98	21.00	7.65	26.38	5.95	23.91	10.01	19.48	10.64	5.44	5.65
	AE post	8.31	5.80	13.27	3.74	27.41	8.98	35.62	9.73	17.97	7.05	24.10	9.48	21.93	8.64	15.89	10.45	6.87	4.45
	RMSE pre	16.25	22.68	22.47	17.40	35.07	12.23	33.13	11.21	29.05	9.15	29.47	5.81	29.31	11.39	23.13	17.90	6.75	6.21
	RMSE post	9.76	6.94	14.93	3.34	29.77	8.19	39.01	9.98	24.63	7.89	28.48	13.63	26.84	10.11	21.10	20.91	9.38	6.84
	SD pre	14.35	22.98	15.30	21.38	20.67	20.27	26.73	14.38	27.72	8.68	30.38	7.52	28.41	16.07	15.82	21.52	5.78	5.00
	SD post	5.98	5.58	9.09	5.94	18.83	12.89	23.58	18.18	22.58	9.11	27.69	14.37	25.76	12.45	18.46	23.98	7.47	6.73
NVG	AE pre	20.67	22.11	24.12	18.71	29.31	15.30	29.59	8.21	22.54	14.42	27.68	12.06	23.99	9.39	16.89	8.91	12.47	13.28
	AE post	14.84	10.80	25.48	19.22	27.95	13.75	32.10	10.54	18.94	9.45	25.98	11.61	23.13	12.64	20.38	9.74	10.66	6.11
	RMSE pre	26.40	30.81	30.28	26.85	34.64	20.33	33.71	9.94	29.89	14.57	33.78	15.03	27.85	10.03	19.46	9.76	15.60	17.44
	RMSE post	20.04	15.55	29.75	25.79	31.19	15.54	34.74	10.63	23.13	10.11	29.14	12.78	26.77	12.84	24.02	13.33	12.70	6.87
	SD pre	20.22	24.03	24.63	26.65	27.08	25.02	30.24	15.20	25.10	11.18	30.62	12.26	25.18	12.62	15.12	10.68	12.42	18.03
	SD post	17.68	17.99	20.32	27.45	18.50	16.31	21.20	9.80	21.59	10.24	23.19	12.84	24.89	14.67	16.08	15.44	7.00	6.37
FVG	AE pre	24.49	24.29	22.60	11.53	23.30	8.13	23.38	6.51	24.17	15.07	29.31	5.29	28.54	11.42	17.09	5.40	12.25	11.49
	AE post	15.81	7.89	14.68	5.99	26.27	11.32	25.10	7.08	20.07	15.99	22.98	7.96	24.95	10.71	16.63	4.97	14.51	11.24
	RMSE pre	29.59	24.49	27.47	17.74	26.98	9.45	26.51	7.38	27.95	13.92	34.12	8.92	33.41	13.15	18.81	4.68	18.74	22.88
	RMSE post	20.69	12.23	17.08	6.95	30.01	11.26	28.11	7.83	24.33	16.77	25.16	8.38	31.48	15.67	18.74	5.26	25.55	24.94
	SD pre	16.23	11.40	23.48	17.39	18.60	10.43	23.85	12.56	29.09	16.37	32.77	12.29	26.94	11.19	13.86	6.49	16.19	23.09
	SD post	14.98	11.40	12.45	10.48	28.90	15.85	22.07	9.89	24.84	18.13	23.03	7.55	31.94	20.03	12.85	5.37	23.91	25.29
CVG	AE pre	22.84	20.69	32.67	34.81	31.62	33.48	27.58	19.75	28.24	12.15	29.06	17.86	28.30	11.87	22.87	21.03	11.00	6.57
	AE post	17.48	10.73	18.78	8.28	22.40	12.12	25.28	9.42	16.69	5.84	22.74	8.31	19.18	4.86	16.75	7.21	17.19	21.48
	RMSE pre	30.94	32.74	40.82	38.28	33.86	32.84	31.21	19.93	32.51	11.91	32.25	18.40	37.58	18.11	26.35	24.73	13.27	8.24
	RMSE post	23.87	19.94	21.48	9.03	24.44	11.86	28.29	10.19	22.97	6.35	25.84	9.31	23.86	7.55	20.38	9.17	26.11	35.93
	SD pre	23.03	28.94	35.07	25.71	19.12	8.27	19.03	6.82	25.60	11.19	23.79	14.23	33.55	20.68	20.10	18.90	8.73	6.48
	SD post	17.31	19.93	13.53	9.55	15.04	9.35	21.33	11.48	21.76	7.18	24.12	9.23	21.00	7.44	14.71	9.50	22.02	32.63

Table 10. *Descriptive Statistics for Temporal Correlation Measures for the Series of Relative Phases in Experiment 2*.

Group	Assessment	Mean α of relative phase	
		Mean	*SD*
CTRL	IE-pre	0.76	0.16
	IE-post	0.76	0.15
	VG	0.58	0.07
NVG	IE-pre	0.78	0.21
	IE-post	0.76	0.18
	VG	0.66	0.10
FVG	IE-pre	0.76	0.14
	IE-post	0.74	0.11
	VG	0.60	0.07
CVG	IE-pre	0.87	0.26
	IE-post	0.81	0.17
	VG	0.55	0.06

Table 11. *Descriptive Statistics for Temporal Correlation Measures for the Series of Amplitudes in Experiment 2.*

Group	Assessment	Mean α of amplitudes	
		Mean	*SD*
CTRL	IE-pre	0.80	0.12
	IE-post	0.79	0.11
	VG	0.64	0.10
NVG	IE-pre	0.89	0.08
	IE-post	0.79	0.23
	VG	0.72	0.11
FVG	IE-pre	0.88	0.12
	IE-post	0.86	0.12
	VG	0.67	0.11
CVG	IE-pre	0.82	0.12
	IE-post	0.87	0.09
	VG	0.47	0.06

Table 12. *Descriptive Statistics for Temporal Correlation Measures for the Series of Periods in Experiment 2.*

Group	Assessment	Mean α of periods	
		Mean	*SD*
CTRL	IE-pre	0.69	0.12
	IE-post	0.69	0.10
	VG	0.73	0.14
NVG	IE-pre	0.74	0.16
	IE-post	0.68	0.10
	VG	0.72	0.14
FVG	IE-pre	0.75	0.09
	IE-post	0.68	0.09
	VG	0.80	0.13
CVG	IE-pre	0.72	0.14
	IE-post	0.74	0.09
	VG	0.78	0.11

Table 13. *Descriptive Statistics for Average Complexity of the Relative Phase Series (Mean Across Scales) Per Condition and Group in Experiment 2.*

Group	Condition	Average Complexity	
		Mean	*SD*
CTRL	IE-pre	1.55	0.11
	IE-post	1.52	0.11
	VG	1.43	0.17
NVG	IE-pre	1.49	0.22
	IE-post	1.54	0.13
	VG	1.52	0.11
FVG	IE-pre	1.62	0.11
	IE-post	1.60	0.09
	VG	1.51	0.13
CVG	IE-pre	1.50	0.16
	IE-post	1.59	0.07
	VG	1.52	0.11

Table 14. *Descriptive Statistics for Average Complexity of the Bivariate Series of Amplitudes (Mean Across Scales) Per Condition and Group in Experiment 2.*

Group	Condition	Average Complexity	
		Mean	*SD*
CTRL	IE-pre	1.50	0.14
	IE-post	1.50	0.09
	VG	1.33	0.17
NVG	IE-pre	1.39	0.33
	IE-post	1.57	0.08
	VG	1.43	0.16
FVG	IE-pre	1.57	0.10
	IE-post	1.66	0.06
	VG	1.49	0.21
CVG	IE-pre	1.44	0.14
	IE-post	1.57	0.10
	VG	1.60	0.11

Table 15. *Descriptive Statistics for Average Complexity of the Bivariate Series of Periods (Mean Across Scales) Per Condition and Group in Experiment 2.*

Group	Condition	Average Complexity	
		Mean	*SD*
CTRL	IE-pre	1.85	0.24
	IE-post	1.94	0.31
	VG	1.33	0.25
NVG	IE-pre	1.62	0.51
	IE-post	1.99	0.36
	VG	1.26	0.41
FVG	IE-pre	1.91	0.52
	IE-post	2.03	0.56
	VG	1.71	0.47
CVG	IE-pre	1.57	0.43
	IE-post	2.01	0.43
	VG	1.89	0.48

Figure Captions

Figure 1. Experimental setup in Experiment 1. See text for details.

Figure 2. Definition of the four events per cycle used in analyses presented in Experiment 1 and Experiment 2.

Figure 3. DFA and $^{low}PSD_{we}$ of the series of relative phases as a function of Condition and Group in Experiment 1.

Figure 4. DFA and $^{low}PSD_{we}$ of the series of amplitudes as a function of Condition and Group in Experiment 1.

Figure 5. DFA and $^{low}PSD_{we}$ of the series of periods as a function of Condition and Group in Experiment 1.

Figure 6. Sample Entropy of series of relative phase as a function of Condition, Group and Scale in Experiment 1.

Figure 7. Multivariate Sample Entropy of the bivariate series of amplitudes (right and left hands) as a function of Condition, Group and Scale in Experiment 1.

Figure 8. Multivariate Sample Entropy of the bivariate series of periods (right and left hands) as a function of Condition, Group and Scale in Experiment 1.

Figure 9. Apparatus used to test haptic perception of relative phase in Experiment 2.

Figure 10. Mean of relative phase as a function of Group, Assessment, Trial, and Practice Day in Experiment 2.

Figure 11. Standard Deviation of relative phase as a function of Group, Assessment, Trial, and Practice Day in Experiment 2.

Figure 12. Root Mean Square Error of relative phase as a function of Group, Assessment, Trial, and Practice Day in Experiment 2.

Figure 13. Mean relative phase as a function of Group and Assessment in Experiment 2.

Figure 14. Standard Deviation of relative phase as a function of Group and Assessment in Experiment 2.

Figure 15. Root Mean Square Error of relative phase as a function of Group and Assessment in Experiment 2.

Figure 16. Absolute Error of Haptic Perception of Relative Phase, pre- and post-training, as a function of relative phase tested (Angle) and Group in Experiment 2.

Figure 17. Root Mean Square Error of Haptic Perception of Relative Phase, pre- and post-training, as a function of relative phase tested (Angle) and Group in Experiment 2.

Figure 18. Standard Deviation of Haptic Perception of Relative Phase, pre- and post-training, as a function of relative phase tested (Angle) and Group in Experiment 2.

Figure 19. DFA of the series of relative phases as a function of Assessment and Group in Experiment 2.

Figure 20. DFA of the series of amplitudes as a function of Assessment and Group in Experiment 2.

Figure 21. Sample Entropy of series of relative phase as a function of Assessment, Group and Scale in Experiment 2.

Figure 22. Multivariate Sample Entropy of the bivariate series of amplitudes (right and left hands) as a function of Assessment, Group and Scale in Experiment 2.

Figure 23. Multivariate Sample Entropy of the bivariate series of periods (right and left hands) as a function of Condition, Group and Scale in Experiment 2.

Figure 24. Illustration of intrinsic mode functions extracted with Empirical Mode Decomposition. Right panel is from Rilling, Flandrin, and Gonçalvés, (2003), reprinted with

author's permission. Left panel contains data from a participant of group A. Note that only the 1st, 4th, 7th and 10th (last) intrinsic mode functions are shown.

Figure 25. Three first panels show the percentage of bad predictions by local dimension as a function of neighborhood size for each Condition in Experiment 1. Bottom left panel shows the percentage of bad predictions averaged across neighborhood sizes for each Condition. In all panels, squares indicate the number of ADF.

Figure 26. Multivariate Sample Entropy curves across scales reveal higher complexity for pink (correlated noise) compared to white (uncorrelated) noise for both the Multivariate Multiscale Entropy (Multivariate MSE) method and Multivariate Empirical Mode Decomposition-enhanced Multivariate Multiscale Entropy (MEMD-enhanced Multivariate MSE) method. From Ahmed et al., 2012, reprinted with permission from the author.

Figure 1.

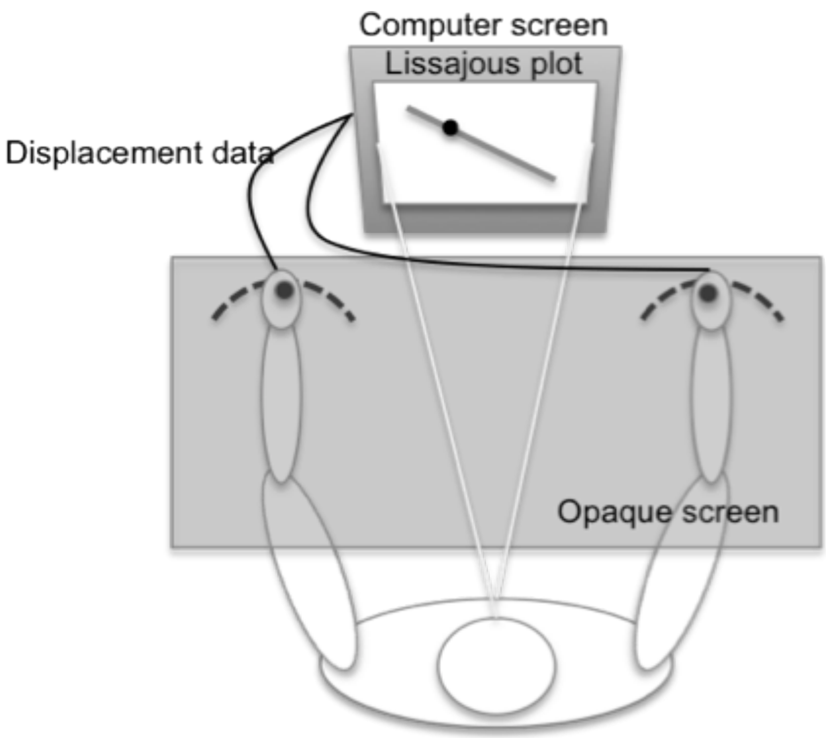

Computer screen
Lissajous plot
Displacement data
Opaque screen

Figure 2.

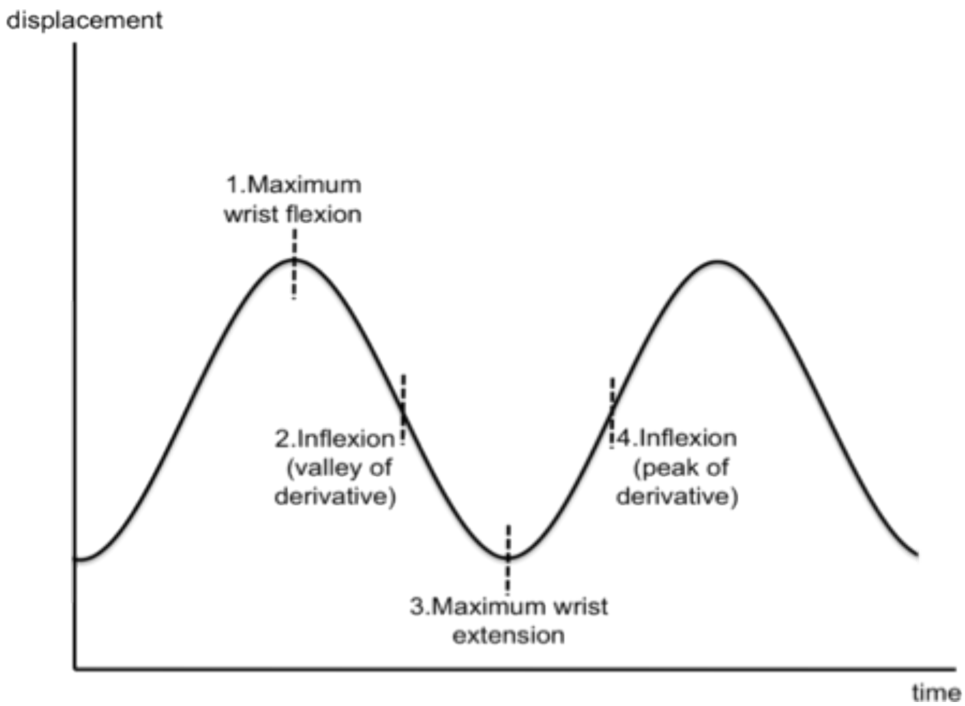
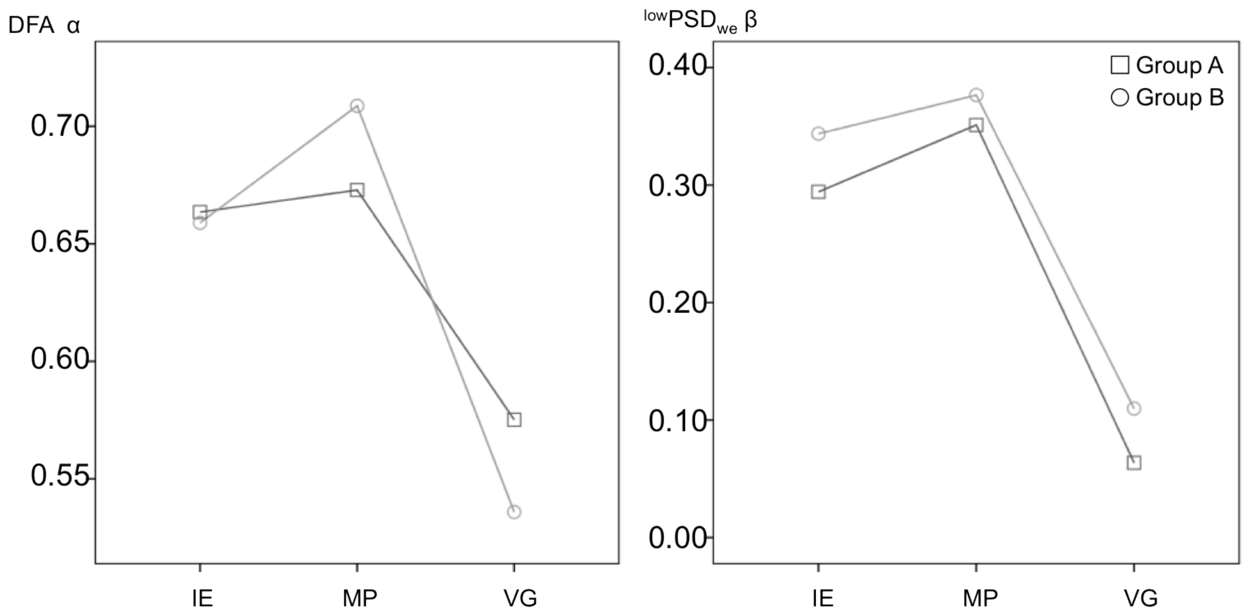

displacement
1.Maximum wrist flexion
2.Inflexion (valley of derivative)
3.Maximum wrist extension
4.Inflexion (peak of derivative)
time

Figure 3.



DFA α
0.70
0.65
0.60
0.55
IE
MP
VG
$^{low}PSD_{we}$ β
0.40
0.30
0.20
0.10
0.00
Group A
Group B
IE
MP
VG

Figure 4.

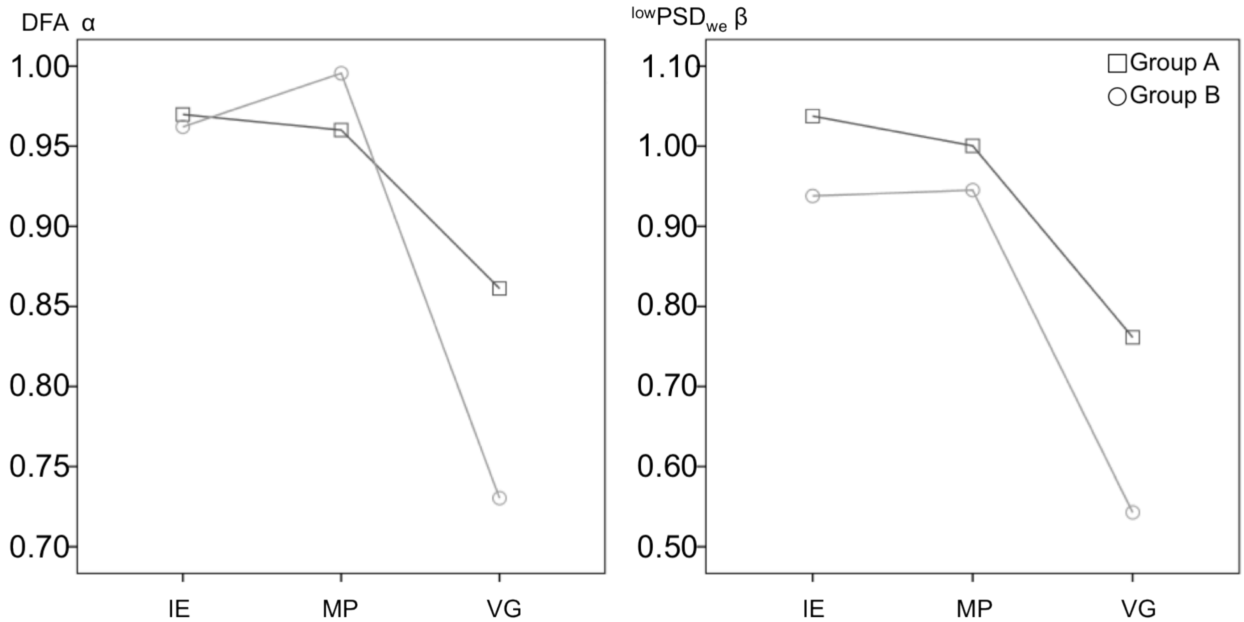
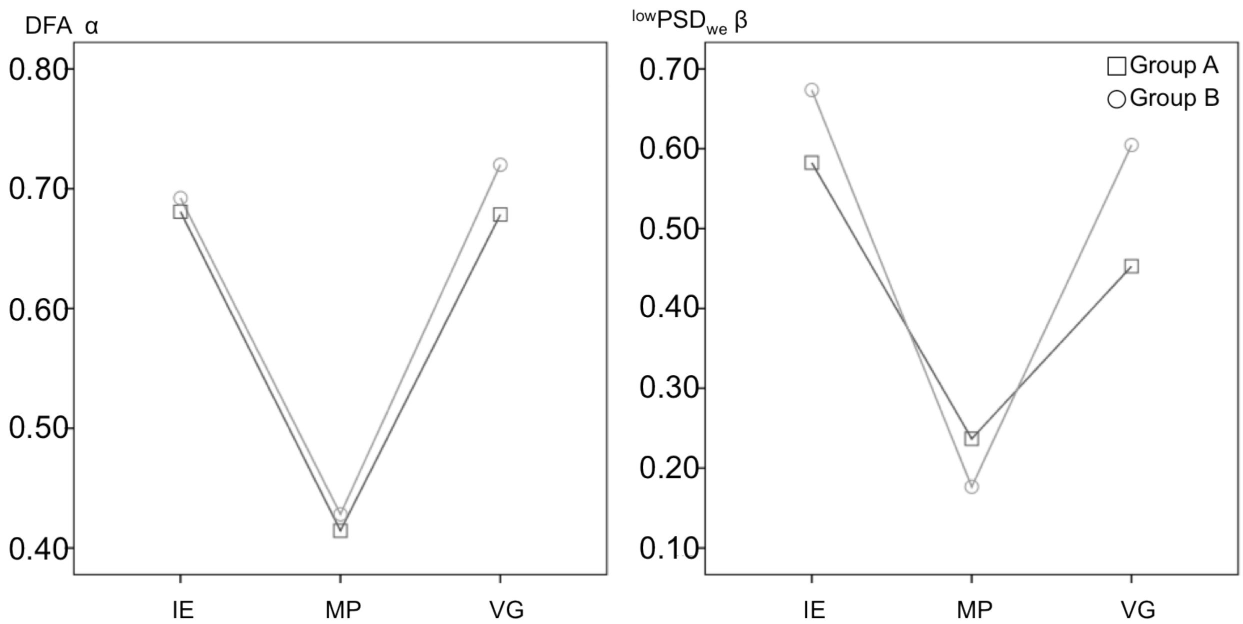
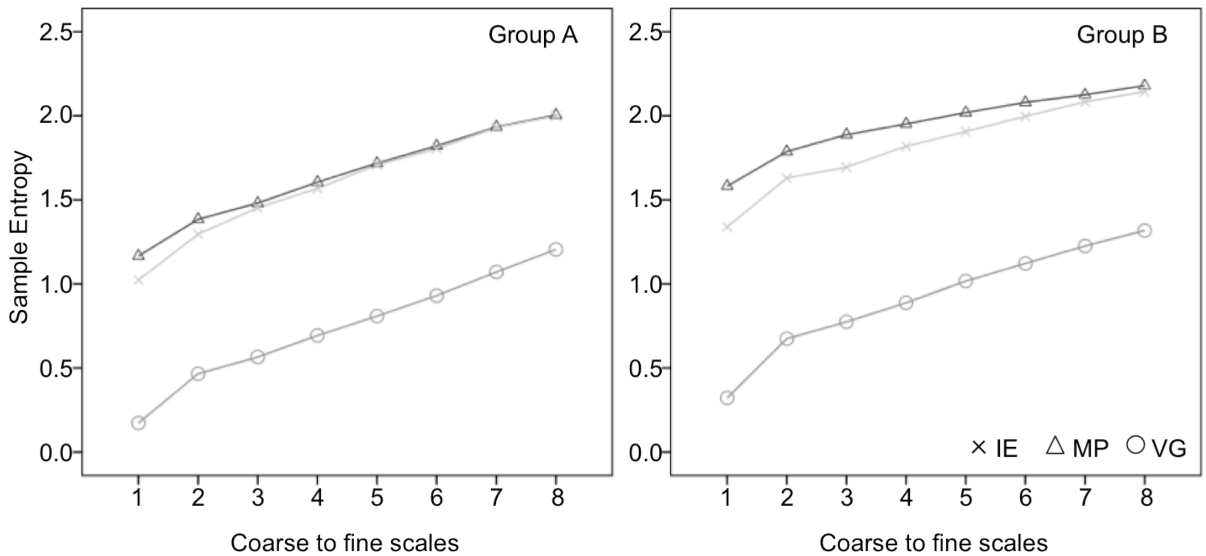

DFA α
1.00
0.95
0.90
0.85
0.80
0.75
0.70
IE
MP
VG
$^{low}PSD_{we}$ β
Group A
Group B
1.10
1.00
0.90
0.80
0.70
0.60
0.50
IE
MP
VG

Figure 5.



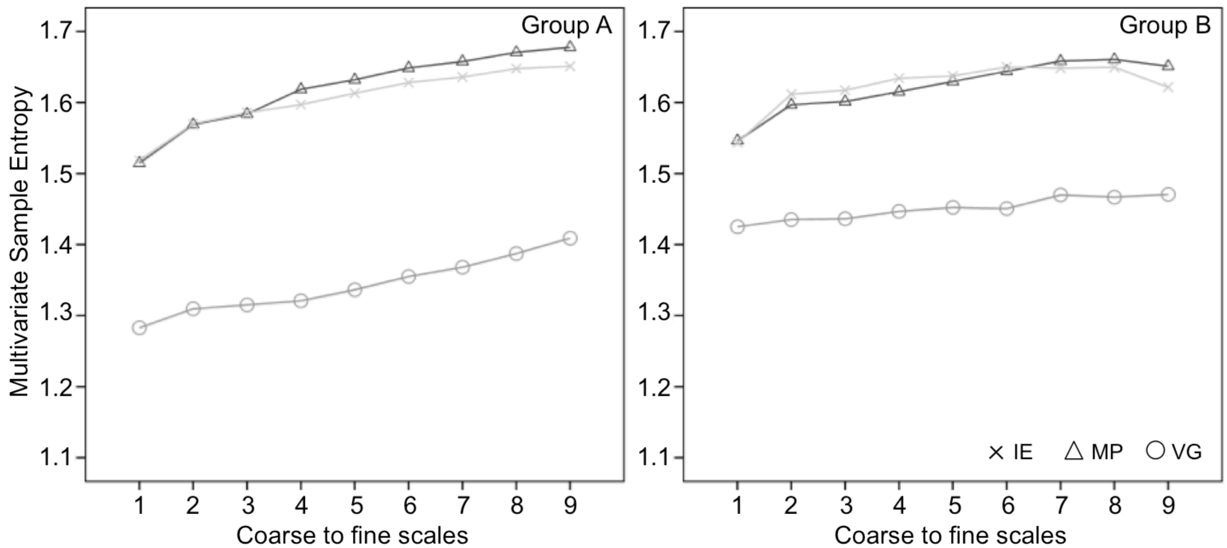
DFA α
0.80
0.70
0.60
0.50
0.40
IE
MP
VG
lowPSDwe β
Group A
Group B
0.70
0.60
0.50
0.40
0.30
0.20
0.10
IE
MP
VG

Figure 6.



Group A
Group B
Sample Entropy
2.5
2.0
1.5
1.0
0.5
0.0
1
2
3
4
5
6
7
8
Coarse to fine scales
× IE
△ MP
○ VG

Figure 7.



Group A
Group B
Multivariate Sample Entropy
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1 2 3 4 5 6 7 8 9
Coarse to fine scales
IE
MP
VG

Figure 8.

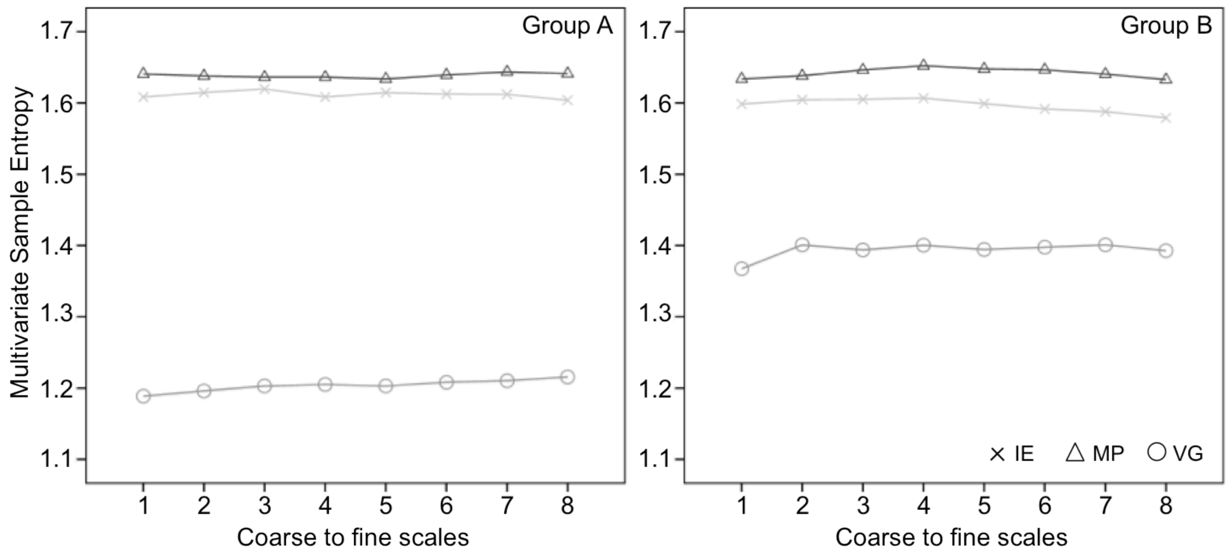

Group A
Group B
Multivariate Sample Entropy
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1
2
3
4
5
6
7
8
Coarse to fine scales
IE
MP
VG

Figure 9.

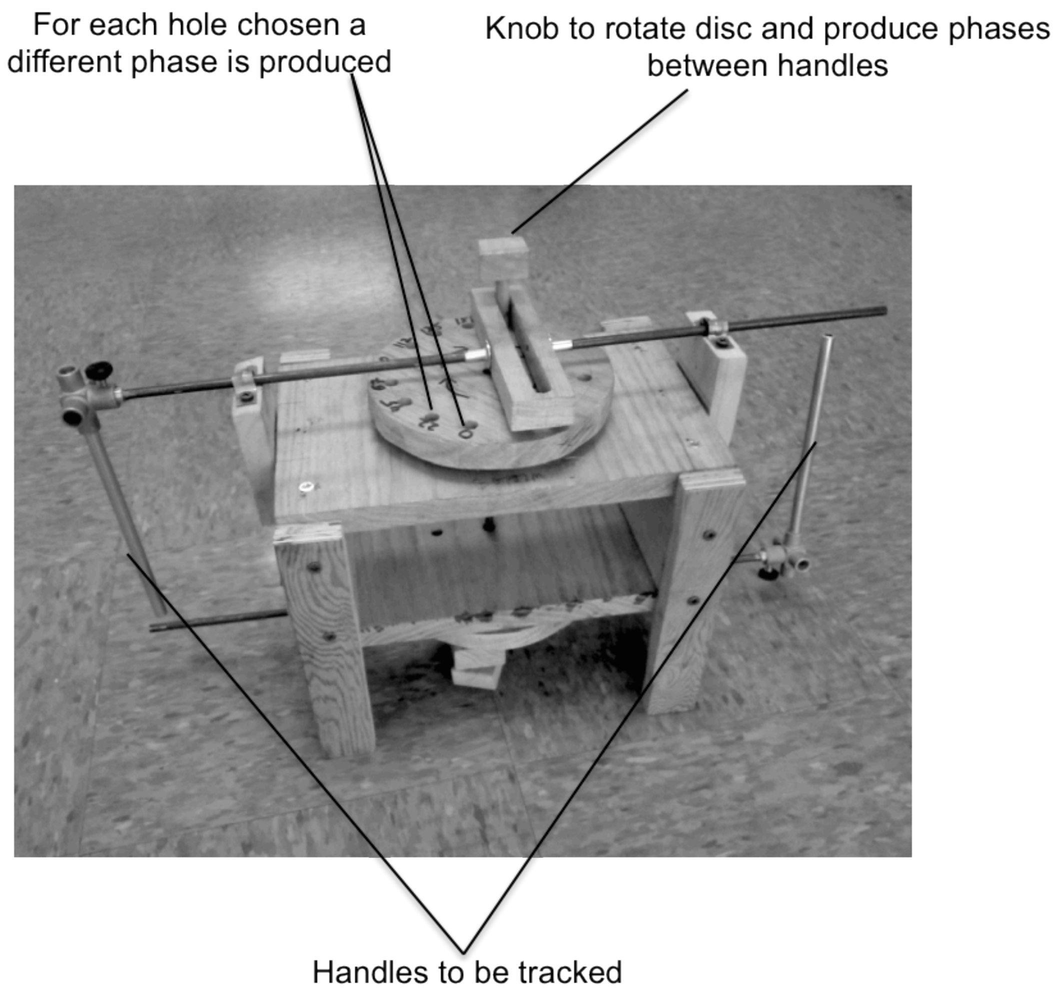

For each hole chosen a different phase is produced
Knob to rotate disc and produce phases between handles
Handles to be tracked

Figure 10. Figure 11. Figure 12.

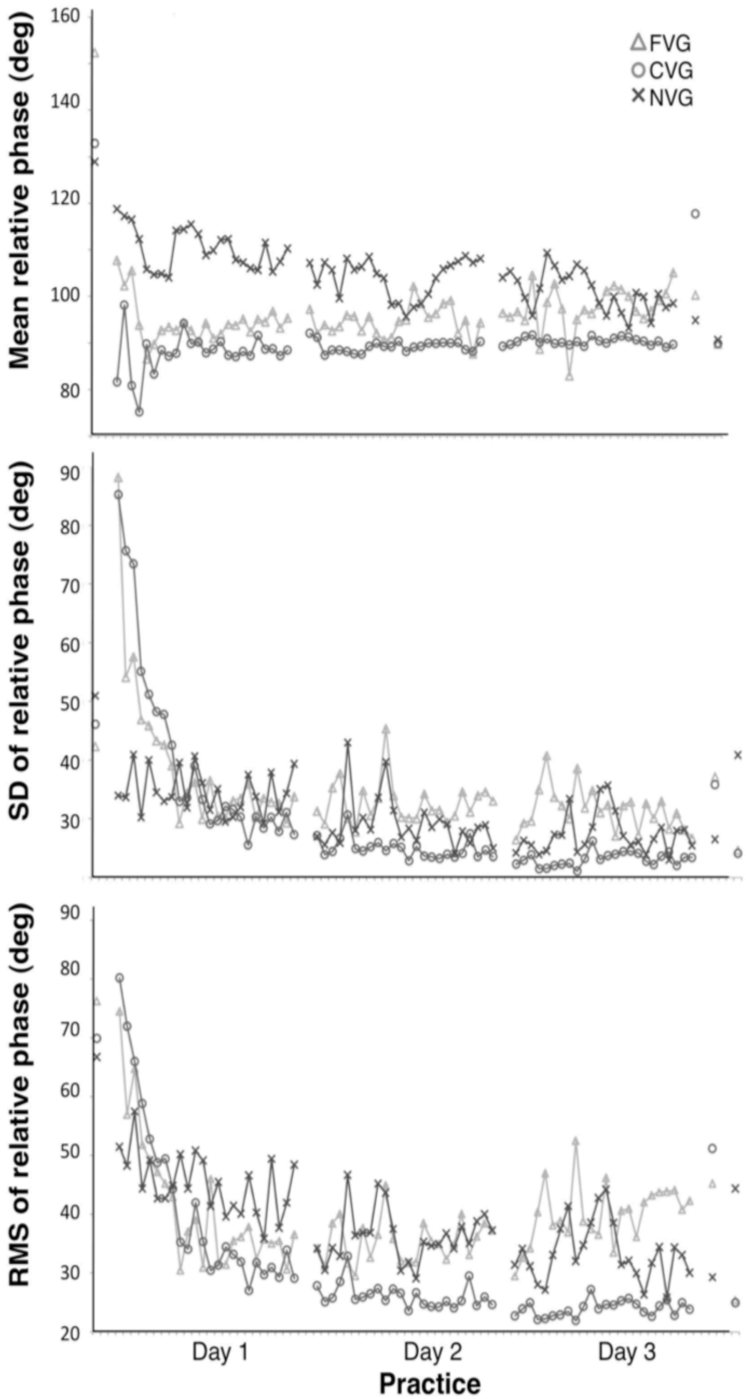


Figure 13.

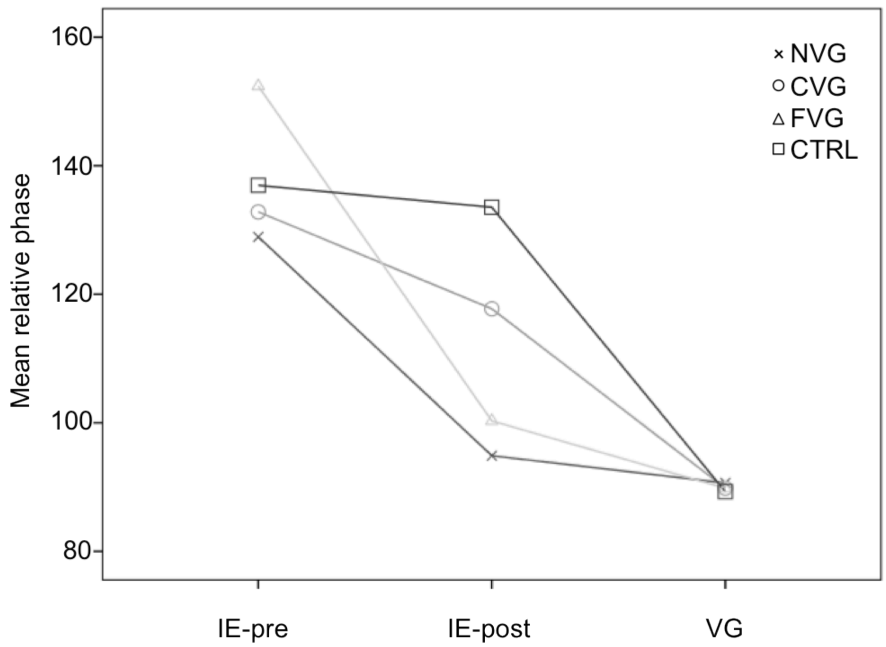

Mean relative phase
160
140
120
100
80
IE-pre
IE-post
VG
NVG
CVG
FVG
CTRL

Figure 14.

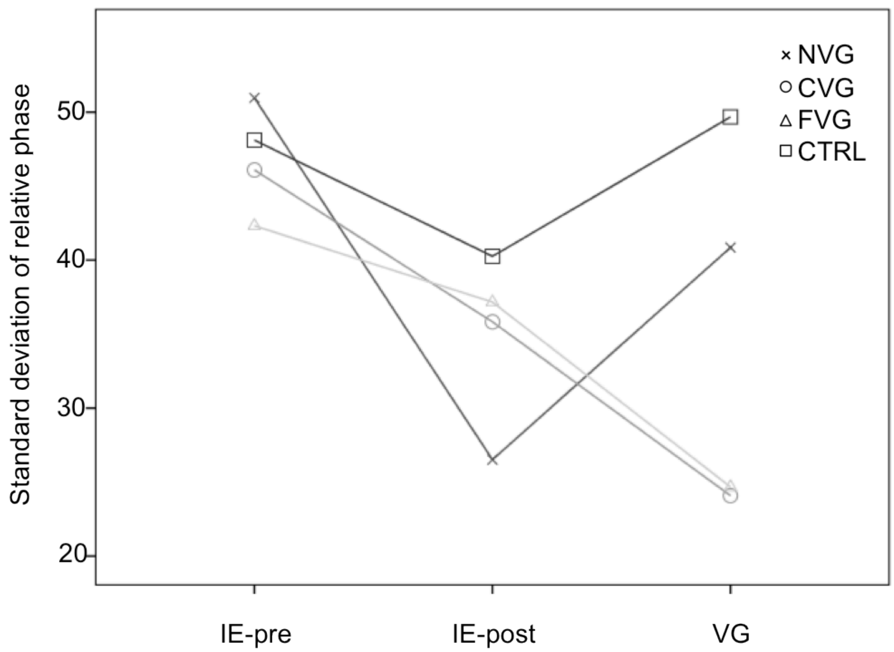

NVG
CVG
FVG
CTRL
Standard deviation of relative phase
50
40
30
20
IE-pre
IE-post
VG

Figure 15.

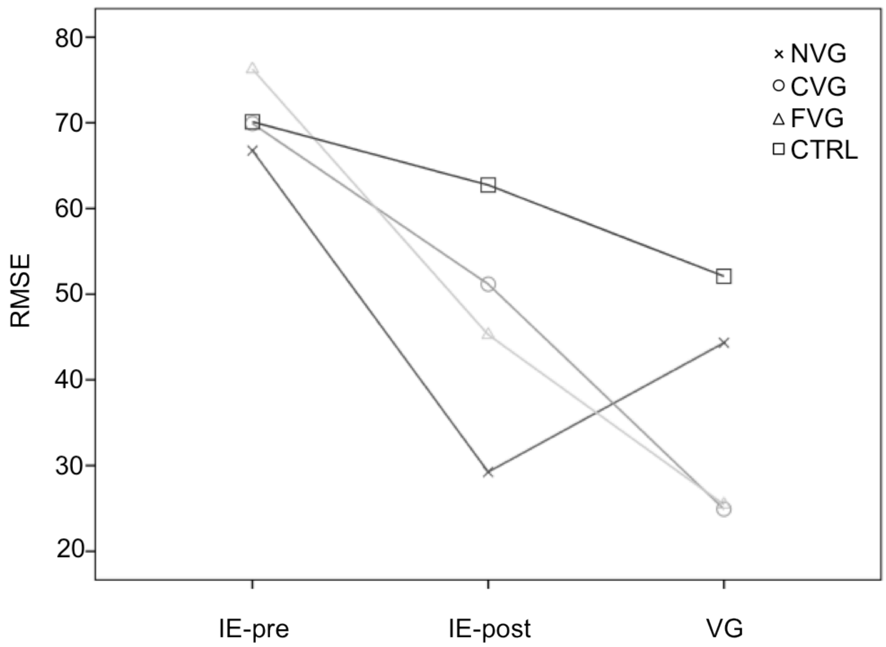
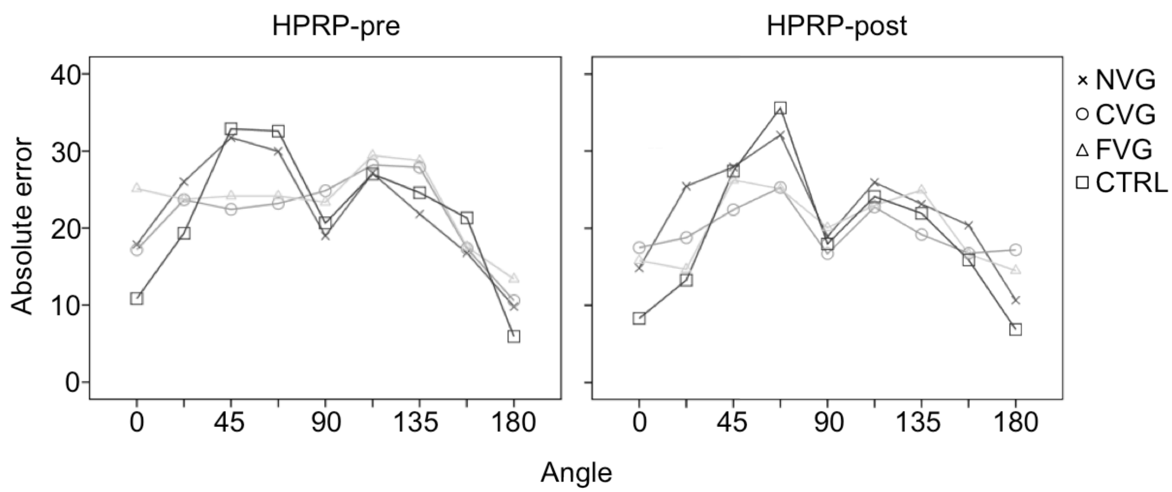
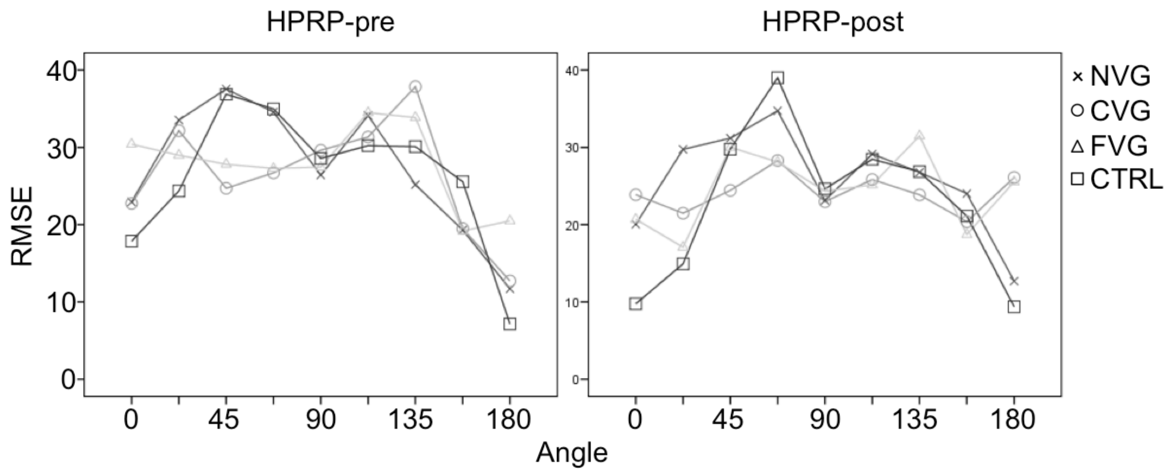


Figure 16.



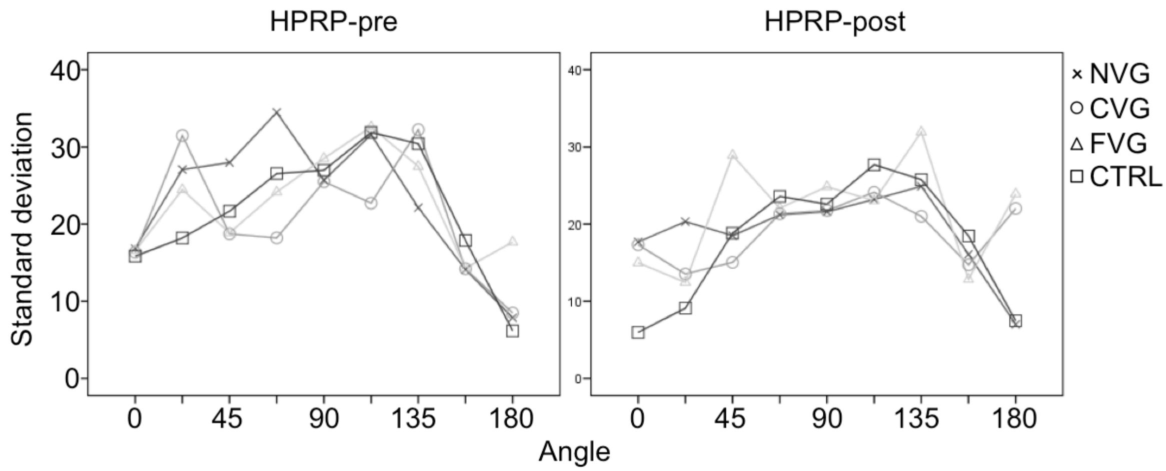
HPRP-pre
HPRP-post
Absolute error
0
10
20
30
40
0
45
90
135
180
Angle
× NVG
○ CVG
△ FVG
□ CTRL

Figure 17.



HPRP-pre
HPRP-post
RMSE
40
30
20
10
0
0
45
90
135
180
Angle
× NVG
○ CVG
△ FVG
□ CTRL

Figure 18.



HPRP-pre
HPRP-post
Standard deviation
40
30
20
10
0
0
45
90
135
180
Angle
× NVG
○ CVG
△ FVG
□ CTRL

Figure 19.

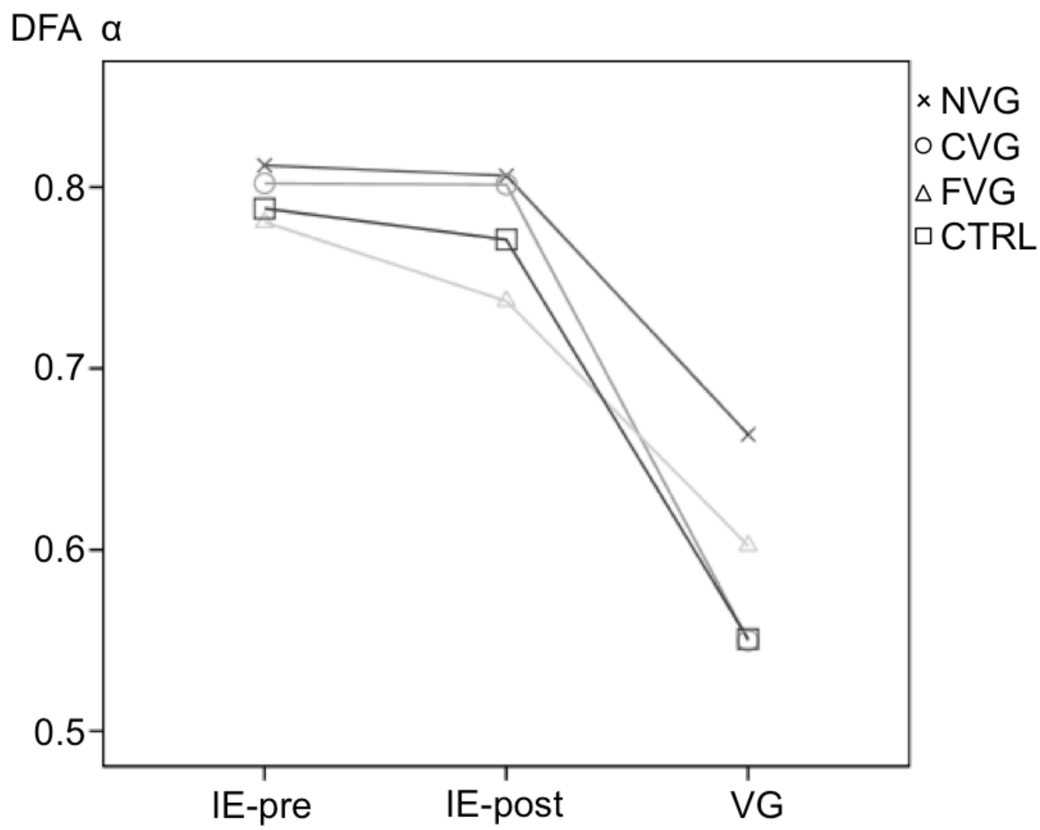


Figure 20.

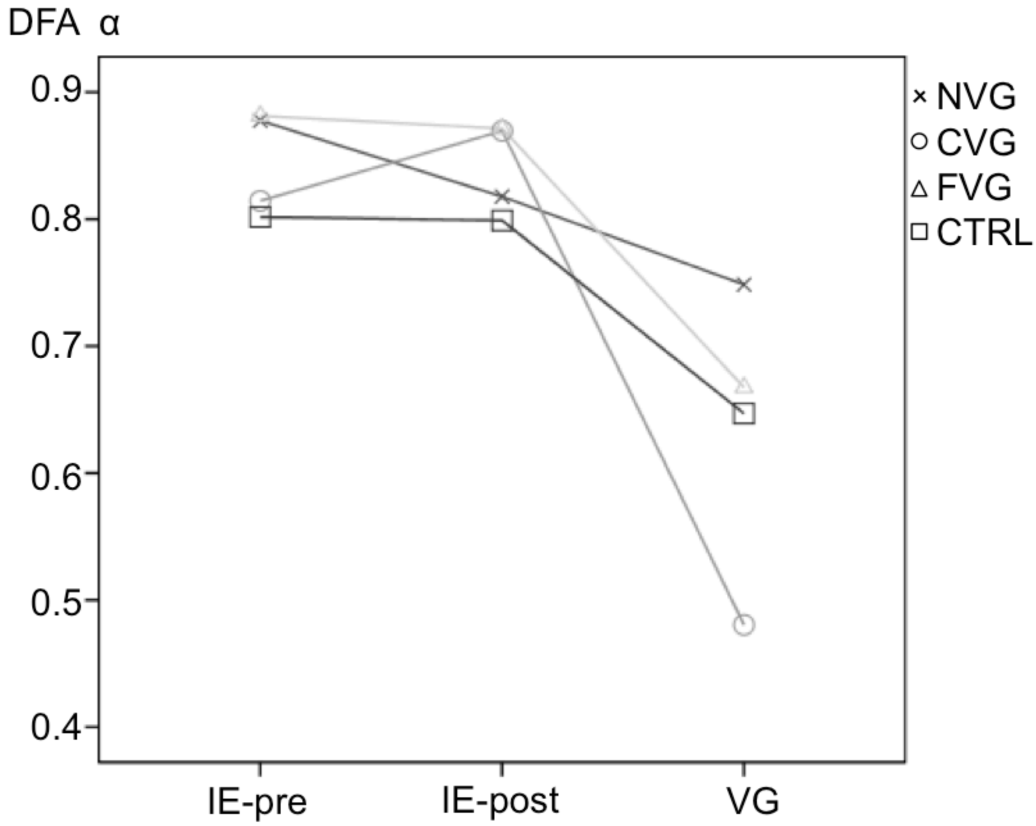
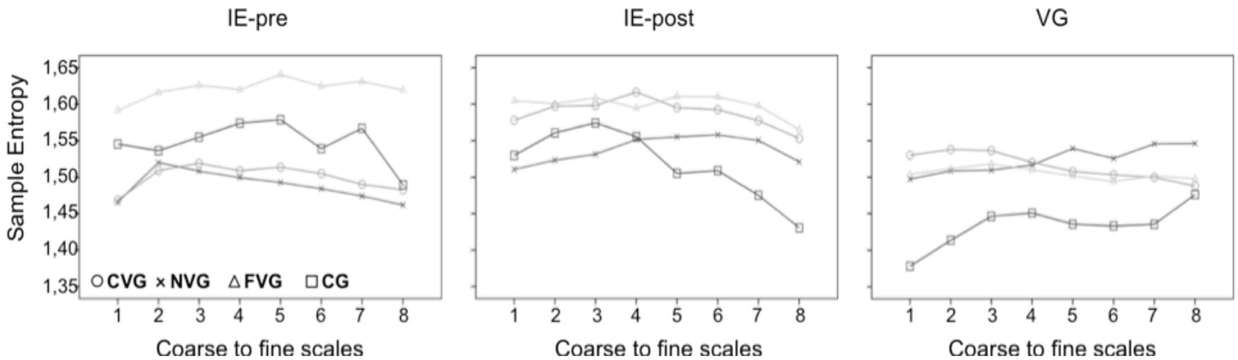
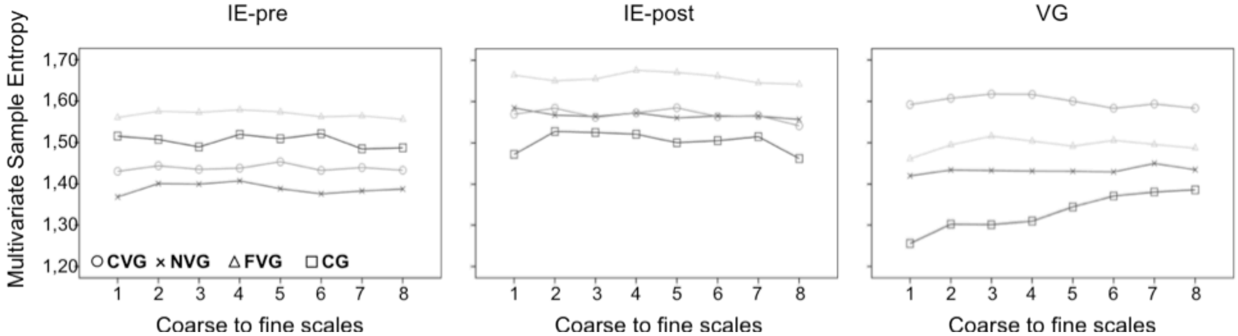


Figure 21.



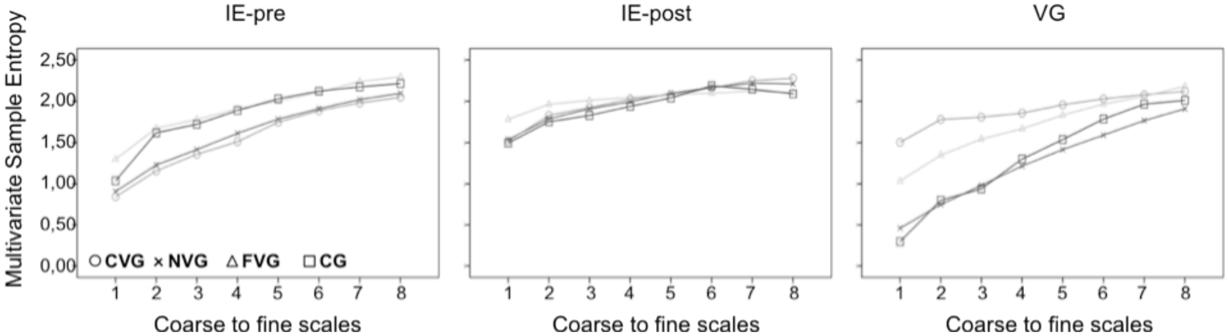
IE-pre
IE-post
VG
Sample Entropy
1,65
1,60
1,55
1,50
1,45
1,40
1,35
CVG
NVG
FVG
CG
1 2 3 4 5 6 7 8
Coarse to fine scales

Figure 22.



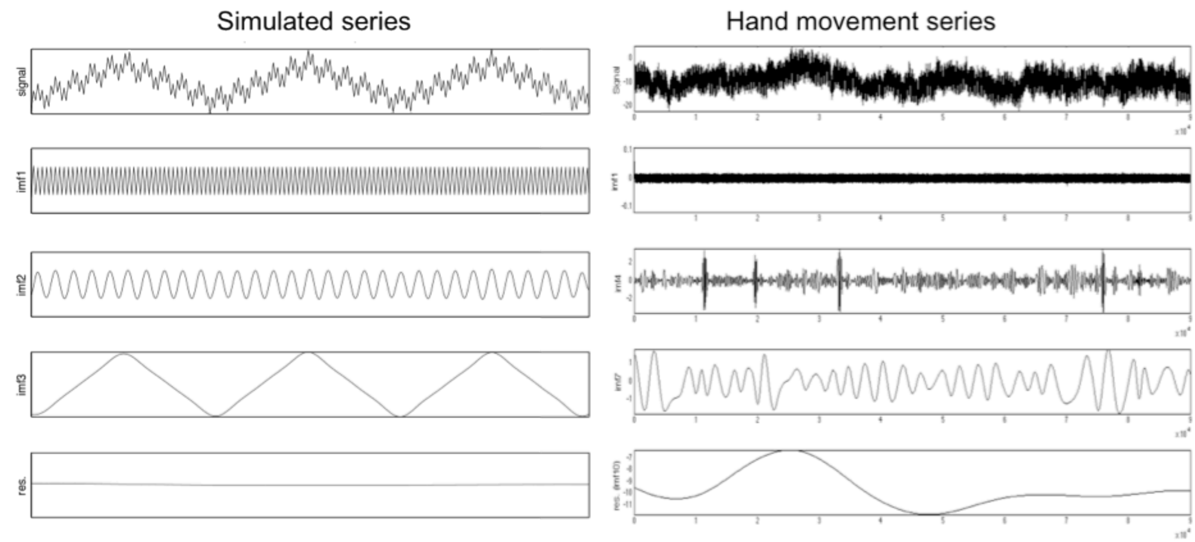
IE-pre
IE-post
VG
Multivariate Sample Entropy
1,70
1,60
1,50
1,40
1,30
1,20
CVG × NVG △ FVG □ CG
1 2 3 4 5 6 7 8
Coarse to fine scales

Figure 23.



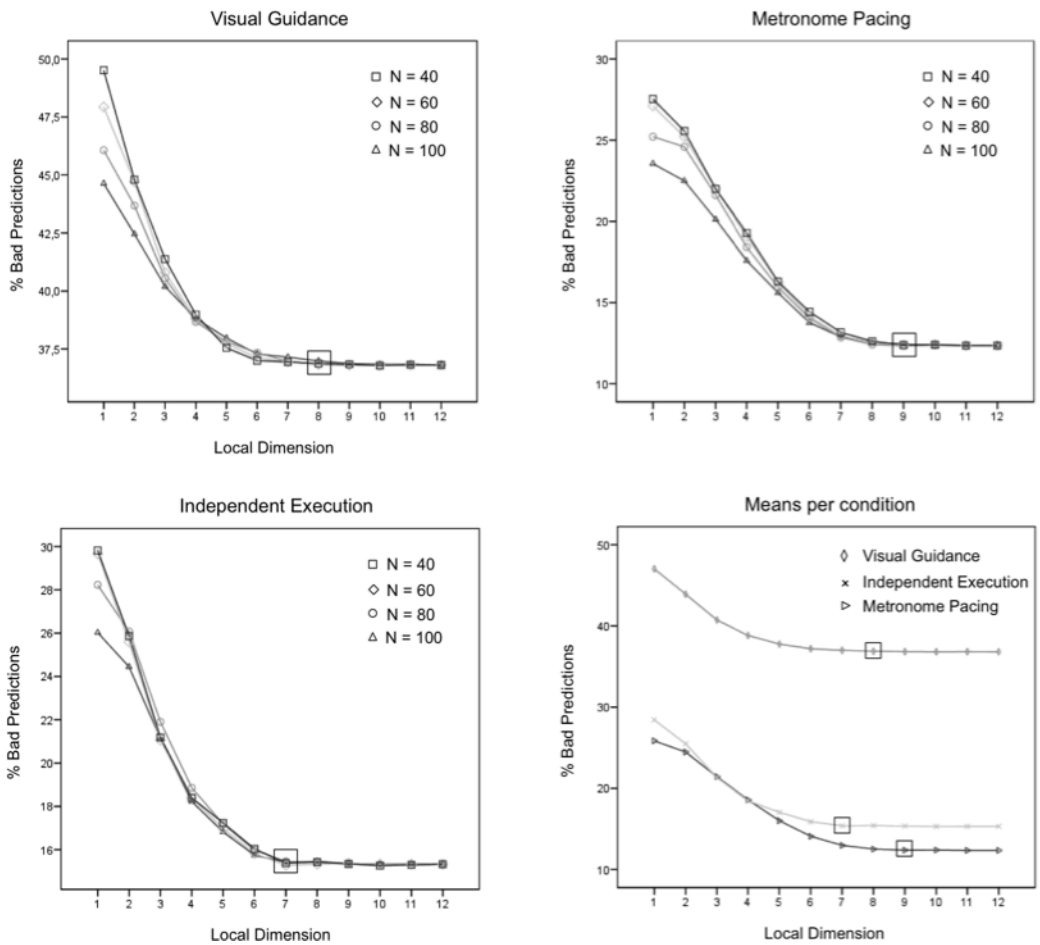
IE-pre
IE-post
VG
Multivariate Sample Entropy
2,50
2,00
1,50
1,00
0,50
0,00
CVG
NVG
FVG
CG
1 2 3 4 5 6 7 8
Coarse to fine scales
Coarse to fine scales
Coarse to fine scales

Figure 24.



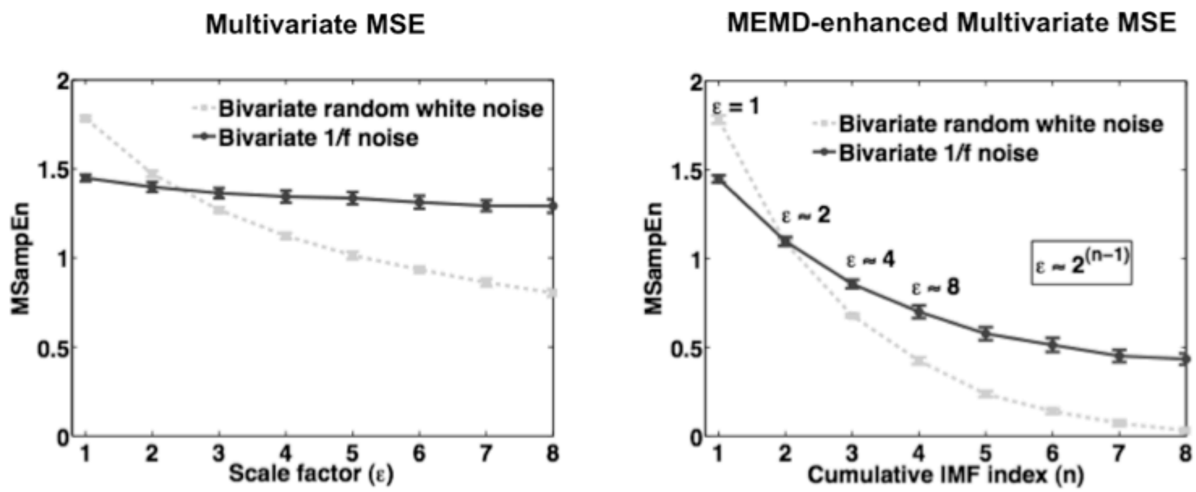
Simulated series
Hand movement series
signal
imf1
imf2
imf3
res.

Figure 25.



Visual Guidance
N = 40
N = 60
N = 80
N = 100
% Bad Predictions
Local Dimension
Metronome Pacing
N = 40
N = 60
N = 80
N = 100
% Bad Predictions
Independent Execution
N = 40
N = 60
N = 80
N = 100
% Bad Predictions
Local Dimension
Means per condition
Visual Guidance
Independent Execution
Metronome Pacing
% Bad Predictions
Local Dimension

Figure 26.



Multivariate MSE
Bivariate random white noise
Bivariate 1/f noise
MSampEn
Scale factor (ε)
MEMD-enhanced Multivariate MSE
ε = 1
ε ≈ 2
ε ≈ 4
ε ≈ 8
ε ≈ 2^(n−1)
Bivariate random white noise
Bivariate 1/f noise
MSampEn
Cumulative IMF index (n)